

FORECASTING CARGO INPUTS TO A
CONTAINER STUFFING STATION

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THESIS

FORECASTING CARGO INPUTS TO A
CONTAINER STUFFING STATION

by

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Forecasting Cargo Inputs to a
Container Stuffing Station

by

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requirements for the degree of

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from the

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December 1974

ABSTRACT

This thesis investigates various techniques for forecasting the volume of containerizable cargo that flows into the container stuffing station at the Military Ocean Terminal, Bay Area, Oakland, California. Cargo input data is analyzed in terms of weekly cargo volume inputs for a selected number of major ports of debarkation. The time-series data for these ports is first tested for serial correlation. Based on the affirmative results of the serial correlation test, the following forecasting methods are investigated: the moving average, the exponentially weighted average, the exponentially weighted average with trend adjustment and the exponentially weighted average with an adaptive response rate. By means of statistical testing procedures, the "best" forecasting method is determined.

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TABLE OF SYMBOLS AND ABBREVIATIONS

ARR	- Adaptive Response Rate
CBL	- Commercial Bill of Lading
CFD	- Container Freight Division, MOTBA
CSS	- Container Stuffing Station, MOTBA
ERL	- Expected Receipt Listing
EWA	- Exponentially Weighted Average
EWA-TA	- Exponentially Weighted Average with Trend Adjustment
GBL	- Government Bill of Lading
LRU	- Less than Release Unit
MAD	- Mean Absolute Deviation
METS	- Mechanized Export Traffic System
MDS	- Mean Deviation Squared
MOTBA	- Marine Ocean Terminal, Bay Area
MSC	- Military Sealift Command
MT	- Measure Ton
POD	- Port of Debarkation
POE	- Port of Embarkation
RU	- Release Unit
SURS	- Surface Export Cargo System
TCDM	- Transportation Control and Movement Document
WAMTMC	- Western Area, Military Traffic Management Command

I. INTRODUCTION

In light of the dispersal of United States forces throughout the world, the shipment of the vast quantities of needed supplies and material to overseas stations is a predominant logistics problem for the Department of Defense. Since the late 1960's the need for efficient and economical handling of this cargo has led the DoD to use containerized shipments on commercial sea-going carriers as the primary routine transportation source. The retention of break bulk type shipping operations has been necessary due to the size limitations of containers. Also, the fulfillment of urgent requirements where time is critical have been met using air transport. However, ocean containerization offers the most cost-effective method of handling routine shipments between ports equipped to handle this type of traffic, as are most Pacific Ocean ports.

The ability to fill or stuff a container at the consignor's warehouse and unpack it at the consignee's warehouse, with no intermediate handling of the cargo, is a tremendous asset. However, many shipments are not large enough to economically warrant their own vans; therefore, stuffing with other shipments bound for the same destination may be accomplished at a central location. One such stuffing facility is the container freight division (CFD) of the Military Ocean Terminal Bay Area (MOTBA) located in Oakland, California. This facility stuffs vans with containerizable

cargo enroute to ports, mainly in the Pacific and the Far East, and arranges transportation of the containers to the ports via commercial carrier.

All commercial carriers require that bookings for vans and space aboard vessels be made in advance of the ship's loading date. As of the fall of 1974, this lead time was at least three weeks. To effectively make these bookings for an advanced date, a prediction of the cargo on hand on the date of arrival of the vans is required. Normally, vans arrive at the stuffing station four to six days prior to the loading date. Thus, the request for space must take into account (1) the present volume of cargo in the warehouse, (2) the forecasted arrivals of cargo during the period between the booking and the van arrivals for stuffing and (3) any previous bookings that will deplete the cargo volume destined for the port during the forecasting period.

The general objective of this thesis is to examine practical forecasting methods which can be utilized to predict cargo arrivals at the container stuffing station. To predict arrivals there are two general approaches that could be used. The first approach is based on notification of shipment departures by consignors, which would provide advanced notice of arrivals at the stuffing station. The other approach is based on historical data, from which projections for future arrivals may be drawn.

An advance notification system does not presently exist for the majority of cargo arriving at the station; however,

it could be produced by requiring consignors to provide the CFD with three-week advance notification of cargo shipments, perhaps by post card. Use of this approach would require analysis of the delay between the arrival of notifications and shipments from each consignor. Also, the statistical characteristics and stability of the transit times for shipments and notifications must be determined. It is doubtful that most consignors have enough advance knowledge of a shipment's departure to provide a timely and accurate notification, especially if the departure is two or three weeks in the future. The effect of the possible lack of consignor cooperation must also be assessed. Taking into account the resources that would be required to effectively implement an advance notification approach, it was decided that forecasting methods which rely only on historical data for future projections would be more appropriate for a thesis topic.

The historical data used here consisted of the cargo arrival data for the CFD for fiscal year 1974; it represented the most recent peacetime data available. The data provided the volume, weight and date of arrival of each shipment. Of the three alternative units for forecasting (number of shipments, volume and weight), the volume of the cargo was selected because it is currently used by the maritime community as the measure for booking containers on vessels.

Two alternative aggregation levels could have been used for forecasting. One was based on the port of debarkation

(POD), and the other based on consignee destination of the cargo. There are more than 1,000 active consignees served by the CFD, which would require a very large number of individual forecasts if the consignee base were used. PODs are the currently used aggregation levels for forecasts by CFD personnel because van space is, by convention, booked aboard ships destined for PODs, not consignees. Therefore, PODs were selected as the aggregation level. Analysis of the data revealed 16 major PODs which received over 90% of the shipments passing through the CFD.

The effectiveness criteria used for the selection of an optimal method are: 1) computational feasibility, and 2) the ability of the method to maximize forecasting accuracy by minimizing forecasting error. Computational feasibility is limited here to those methods which do not require the use of a computer to routinely generate forecasts. Mean absolute deviation and mean deviation squared are used as measures of forecast errors.

Forecast errors were computed over time horizons of one, two and three weeks, corresponding to possible lead times in the booking process. In other words, for a two-week time horizon a single forecast was used for two successive weeks. The deviation for the forecast was computed by taking the average difference between the forecast and the actual input volume for each of the weeks covered by the forecast.

Generally, the selection among various methods of forecasting depends upon the statistical characteristics of the

data. These characteristics are differentiated by the degree of statistical dependence between successive observations. If there is no statistical dependence between successive observations, then ordinary trending and indexing techniques may be applied. On the other hand, the presence of statistical dependence among successive observations, (called serial correlation), implies a need for methods which place more emphasis on recent past observations when predicting future volumes.

Tests for serial correlation of the data for the major PODs were made using the Durbin-Watson d-statistic. The aggregated results of these tests indicated that the presence of serial correlation was statistically significant.

Figure 1 is a graph of the weekly input volumes of POD UL7 for a 20-week period commencing with the nineteenth week of FY '74. This was selected as a typical representation of the data for the major PODs. This particular POD exhibited strong positive serial correlation.

With the existence of serial correlation in the data confirmed, the moving average technique and three exponentially weighted average techniques were examined for prediction accuracy. These methods were chosen for their relative ease of computation and ability to adapt to changes in volume inputs over time.

Simple moving averages [Ref. 5] of from one to ten week durations were the first methods explored. In each method, the most recent weeks for the designated duration are averaged and the result applied to the forecast through the

Volume in
cubic feet

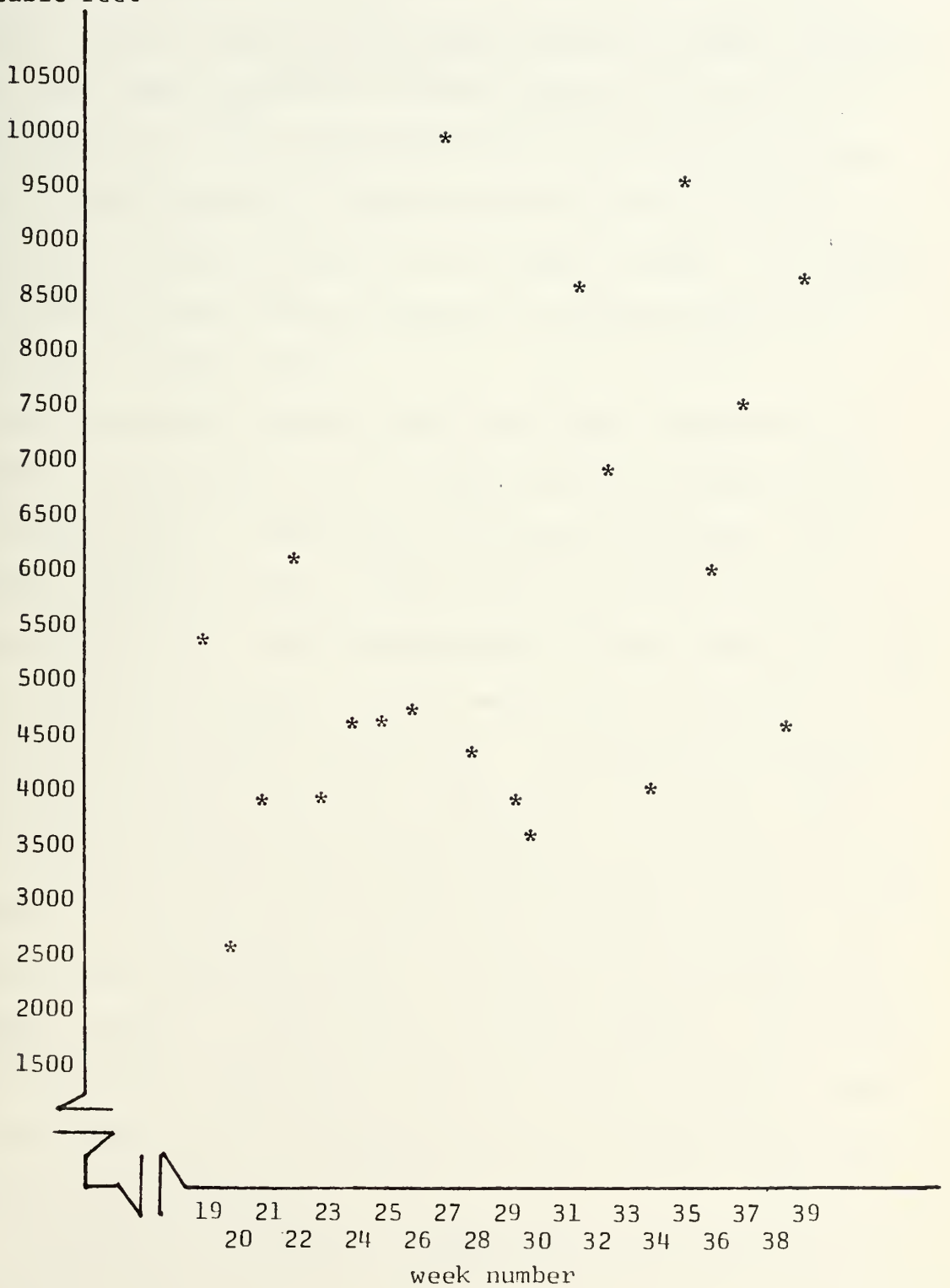


Figure 1: Weekly volume inputs for POD UL7

designated horizon. The three-week moving average was the technique in actual use at the CFD. The resulting data indicated that for all time horizons, moving averages greater than three weeks generally provided lower deviations and thus, better forecasts than the three-week moving average. Note that the longer the duration of the average, the less responsive the predictions are to recent changes. The data indicated that over-sensitivity was as undesirable as no sensitivity in most cases.

The next method examined was the simple exponentially weighted average, [Ref. 5], or exponential smoothing method. This method used a weighting or smoothing constant, alpha, a value usually between zero and one, to regulate the emphasis on the most recent observation. Large values of alpha place increasing emphasis on the most recent observations and less on preceding observations. A forecasted average for an observation period was computed as the sum of the observations in that period times alpha, plus the forecasted average for the previous period times one minus alpha. In this way, the new observation was added to the accumulated weighted average, a continually changing number. This forecast average was then used as the forecast and applied over the next weeks of the designated horizon and the deviation statistics accumulated.

To discover the levels of alpha which minimized error measurement, the levels of alphas were varied by 0.01 from -0.1 to 1.0, and applied to the data for each POD and horizon. The alpha levels which produced minimal deviation

statistics ranged from -0.02 to +0.77 depending on the POD and time horizon specified. The optimal single alpha level for all PODs was about 0.35 and varied slightly depending on the time horizon.

The next forecasting method explored was the exponentially weighted average with adjustment for trends [Ref. 5]. This procedure was examined to determine if trend adjustments would reduce forecast error. This procedure started with the same basic formula as the simple exponentially weighted average, however a trend factor is also computed. This trend is accumulated and smoothed in the same manner as was applied to the forecast averages, resulting in an average trend adjustment. The forecast volume to be used in the predictions was created by combining the forecasted average with the average trend adjustment.

To obtain minimal errors, alpha levels were again varied by 0.01 from -0.10 to 1.00 and the method applied to the data for all PODs. The results revealed minimized deviations for alpha levels between -0.01 and 0.38, again, depending on the POD and time horizon specified. When accounting for trends, the optimal single alpha level for all PODs was 0.16, varying slightly for the different time horizons.

The final forecasting procedure used was the exponentially weighted average using an adaptive response rate technique to modify the alpha level used from period to period to account for fluctuations in the observations [Ref. 18]. The absolute and actual errors, or deviations

and actual errors between the observed and forecasted volumes were separately accumulated and smoothed in the same fashion as the forecast average using a smoothing constant, γ . A tracking signal was then computed by dividing the smoothed absolute error by the smoothed error. Deviation statistics using the simple exponentially weighted average were computed with the alpha level for each forecast set at the absolute value of the tracking signal.

To evaluate the adaptive response rate method, it was applied to the data for each of the PODs while varying the time horizon and the level of the smoothing constant, γ , by 0.01 from -1.00 to 1.00. Here the use of negative constants indicates that the new smoothed error term is created by enlarging the old smoothed error and adding or subtracting a portion of the new error to it. The minimum deviation statistics for the individual POD and various time horizons were realized with γ levels ranging from -1.00 to 0.49. The resultant optimal single γ level for all POD was about -0.05 depending on the horizon used.

In summary, the experimentation with the above forecasting methods had created deviation statistics for the following forecasting procedures:

- 1) Three-week moving averages (maintenance of status quo);
- 2) Moving averages with a single, aggregately optimal duration;
- 3) Moving averages with the optimal duration for each POD;

- 4) Simple exponentially weighted averages using a single, aggregately optimal alpha level;
- 5) Simple exponentially weighted averages using individually optimal alpha levels for each POD;
- 6) Exponentially weighted averages with trend adjustment using a single, aggregately optimal alpha level;
- 7) Exponentially weighted averages with trend adjustment using individually optimal alpha levels for each POD;
- 8) Exponentially weighted averages with adaptive response rates using a single, aggregately optimal gamma level;
- 9) Exponentially weighted averages with adaptive response rates using individually optimal gamma levels for each POD.

Using these deviation statistics, the selection of the "best" forecasting method was made subject to the following considerations:

- 1) For operational consistency, it was assumed that only one of the methods would be chosen for use with all PODs. No attempt was made to evaluate the problem by choosing the optimal forecasting method for each POD.
- 2) The deviation statistics for the one week time horizon were used in the evaluation as the relative effectiveness of the various methods for each POD.
- 3) The mean absolute deviation statistic was selected as the principal goodness criterion since no extra penalties for large individual forecast errors were intended.

In the end, statistical significance tests are used to reveal whether the mean absolute deviations using one forecasting method were significantly less than the deviations of another method. The tests were conducted at a significance level of 0.05. The results indicated that the simple exponentially weighted average and adaptive response rate methods were not significantly different from each other. However, both methods were better than any of the others.

Based on the above results the use of the simple exponentially weighted average was chosen. The selection was founded on the ease of computation of the forecast, as the adaptive response rate method required many more steps for each calculation and offered no better results. Additionally, the adaptive response rate method required a broad range of gamma levels and was characterized by multi-modal relationships between the gamma level and MAD for most cases of PODs and time horizons. This indicated great sensitivity of accuracy to the gamma levels for particular data sets.

When compared to the three-week moving average, the use of this simple exponentially weighted average technique provided 4.9%, 8.0% and 10.0% reductions in mean absolute deviations for the one-, two- and three-week time horizons respectively. In addition to increasing the forecast accuracy the exponentially weighted average is also as easy computationally as the three-week moving average. Operational benefits of the increased forecast accuracy are a reduction in the average age of cargo and volume of cargo in the warehouse, and increased cube utilization.

II. BACKGROUND

A. THE BEGINNING OF CONTAINERIZATION

While containers had been used for transporting cargo aboard vessels as early as the 1820's, the modern era of containerization began in 1966 when Malcolm McLean of Sea-Land Service, Inc., began loading containers aboard ships bound for Europe. The economics of containerization soon became apparent. By the end of 1968, one-fourth to one-third of shipments on major U.S. routes were containerized. American-flag operators as well as their foreign-flag competitors began to invest heavily in the containerized system. This system includes not only containers, but also specialized ships, container terminals and road equipment.

Within the industry the container came to be called the greatest thing in packaging since the paper bag. Most containers are simple boxes of plywood or aluminum and are manufactured in standard sizes: approximately 8 feet wide, 8 feet deep and various lengths between 20 to 40 feet long. The container volume capacity ranges from 1,100 cubic feet to 2,400 cubic feet, and weight capacity ranges from 38,000 pounds to 46,000 pounds depending on the size of the van.

Containerization required the shipping industry to adopt an entirely new line of thinking and provided the industry with many phases of economic improvement: more efficiency in cargo and terminal handling, a reduction in merchandise damage due to weather and handling, a reduction

in terminal facility requirements, a savings in reduced special packaging for export, a reduction in pilferage and other losses, the ability of manufacturers to operate with reduced inventory, and the benefit of computerized inventory-control systems.

Containerization has cut shiploading and unloading time from as much as eight days to as little as twelve hours. The varied forms of containerization are enabling cargo ships to spend as many as nine out of every ten days' productivity at sea instead of half their time in port -- causing some shipping lines to have alternating crews so that the men can spend some time with their families. A typical containership is loaded with some 700 vans, seven deep and six across, and is on its way at 22 knots.

The new era has resulted in transmodal systems to move cargo via land, sea and air with computerized efficiency. In some cases, overall transport costs are down 30-40% as compared to conventional break bulk cargo handling.

Sea-Land Service, Inc., has become the biggest container operator in the world and is one of the two largest U.S. steamship lines. Sea-Land has five 33-knot containerships with capacity for 1,082 units. With other carriers taking advantage of container economics, the United States flag carriers have become the world's largest containership fleet.

The port of Oakland, California is now the leading West Coast cargo shipping terminal -- mainly due to containerization. The port handles 45% of all container shipping on

the West Coast and is the second largest container port in the world -- New York being the largest.

According to James L. Reynolds, President of the American Institute of Merchant Shipping (AIMS), by 1976 cargo moving to and from U.S. ports is expected to rise to 270 million measurement tons (a unit of volume representing 40 cubic feet) plus 7.5 million in military cargo and another 20.5 million in government impelled cargo such as foreign aid shipments.

Containerization has been recognized as a system that will best serve the needs of the public and the transportation industry. The container revolution stems from the immense transportation capability gained from moving goods swiftly, safely and reliably.

B. CONTAINERIZATION AND THE DEPARTMENT OF DEFENSE

In recent years the United States Department of Defense has used commercial containerization as the primary means of transporting its general ocean cargo. Substantial cost savings from the use of containerships in lieu of using the traditional break bulk cargo ships have been recognized. Yet, there still remain problems for transportation officials within DoD to reckon with.

Figure 2 illustrates the portion of the transportation system within the Department of Defense to which this thesis addresses itself.

Orders are placed by DoD overseas commands known as consignees. Various vendors and military depots known as

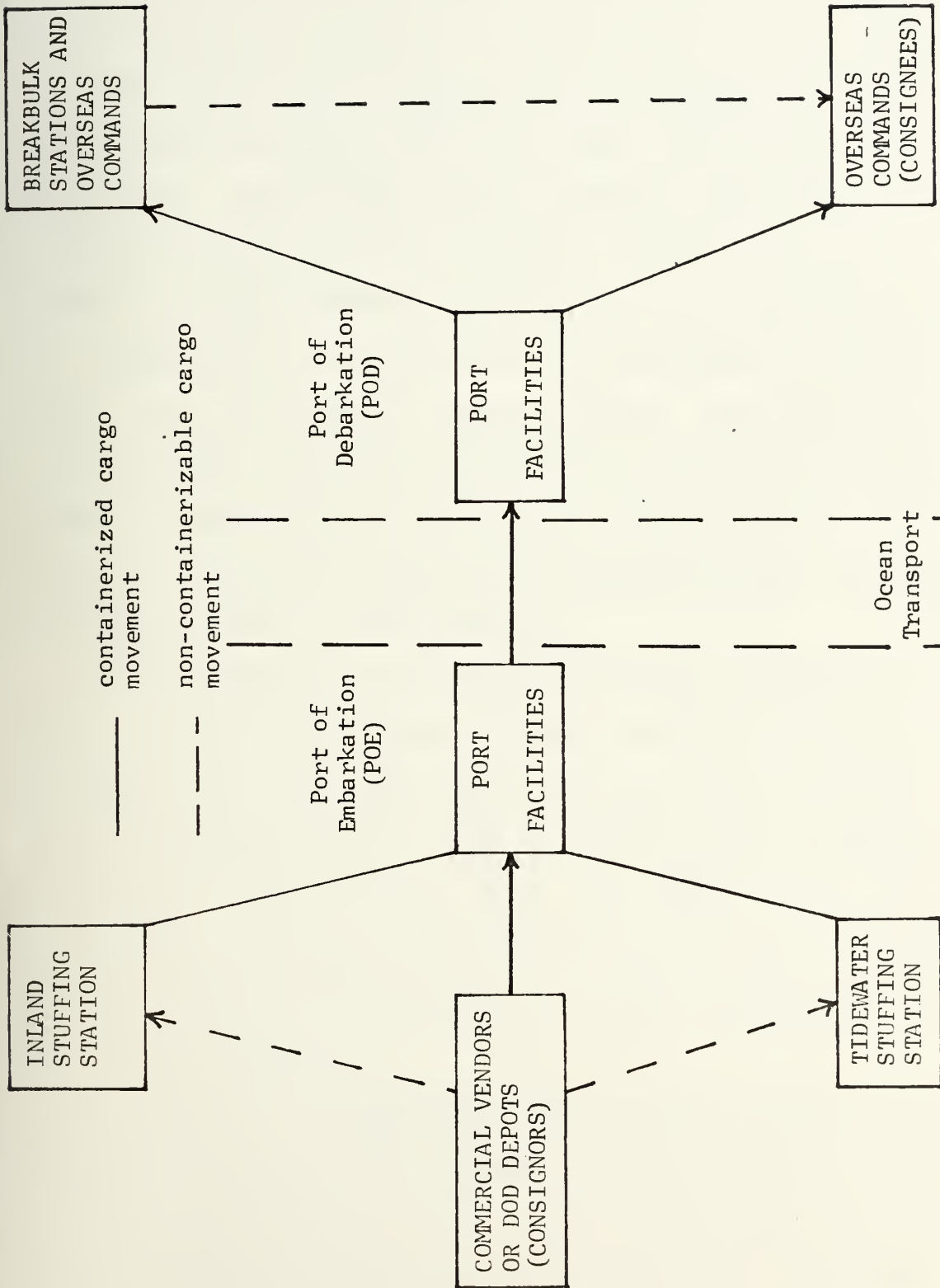


Figure 2: Export Cargo Movement

consignors, fill these purchase orders which the consignees need to execute their missions. It now becomes the job of the DoD transportation managers to deliver these items to the consignee.

Cargo leaving the consignor for the consignee may be transported across the ocean in either container or break bulk ships. Conventional ships transport break bulk cargo to the requesting overseas command. If the goods are ordered in large enough quantities and are containerizable, the consignor may place the cargo in containers at his warehouse. This is known as source stuffing. The sealed container is then shipped to the POE where it has been booked aboard a containership for overseas transport to the consignee. This type of operation provides the most rapid and economical form of ocean shipping.

Another situation occurs when container stuffing stations, at the POE or inland, receive quantities of containerizable cargo for consolidated stuffing into containers. At the stuffing station, cargo for particular consignees is stuffed only after meeting volume and weight restrictions. A commercial shipping company then receives the containers from the stuffing station for lift aboard containerships and overseas transport.

At the Port of Debrakation (POD) single consignee containers are sent directly to the respective consignees. Containers with cargo for more than one consignee are transported to designated break bulk stations (BBS), which may itself by a consignee, where they are broken down for further shipment to individual consignees.

C. WESTERN AREA, MILITARY TRAFFIC MANAGEMENT COMMAND

Western Area, Military Traffic Management Command (WAMTMC) is a jointly-staffed field organization under Headquarters, Military Traffic Management (MTMC), Washington, D. C. WAMTMC is responsible for transporting export cargo of the Department of Defense and other government agencies to overseas commands. It has been located at the Oakland Army Base, Oakland, California, since being established in February 1965. MTMC is a major field command of the Department of the Army.

WAMTMC is responsible for transportation management of domestic and export shipments in 14 western states: Idaho, Arizona, California, Montana, Nevada, Oregon, Utah, New Mexico, Washington, Colorado, Nebraska, South Dakota, North Dakota and Wyoming. One of the three Military Ocean Terminals operated by WAMTMC on the West Coast will receive export cargo from these 14 states which is destined for shipment to overseas installations. The three terminals operated by WAMTMC are: Military Terminal Unit, Pacific Northwest, Seattle, Washington (PNW); Military Ocean Terminal, Bay Area, Oakland, California (MOTBA); Southern California Outport, Long Beach, California (SCO). During peacetime, WAMTMC also directs the flow of all air cargo in the Military Airlift Command's transportation system through the Military Airlift Clearance Authority (MACA).

D. MILITARY OCEAN TERMINAL, BAY AREA

Military Ocean Terminal, Bay Area is the consolidation of the Army and Navy terminal facilities in the San Francisco

Bay Area. It represents the largest operating unit of WAMTMC with terminal facilities at the Oakland Army Base and the Alameda Reefer Facility. Seven deep water berths are under its control as well as an 84-acre tidewater container stuffing area located at the Oakland Army Base. Also under MOTBA's control are the ports of Stockton, Sacramento, and Eureka.

E. TIDEWATER CONTAINER STUFFING STATION

The Container Stuffing Station (CSS) operates under the Container Freight Division (CFD) at MOTBA. Containerizable cargo is loaded into the shipping containers at both installations. These containers are then transferred to the commercial shipping companies for shipment to overseas commands.

The CSS is operated under civilian contract. Containerizable cargo is placed in warehouses until containers become available for stuffing. In most cases commercial containers are used for stuffing, although military vans are sometimes used. The contractor has certain restrictions on container stuffing. Some examples are cargo mix, container utilization, and consignee mixing limitations. In addition, volume, weight and size of containers vary among the various commercial carriers. There are 16 types of containers presently in use; and, in general, each company can accommodate only those containers which have been specifically designed for its vessels.

F. MILITARY SEALIFT COMMAND, PACIFIC

The Military Sealift Command (MSC) is an agency that coordinates the various ocean transportation activities of the Department of Defense. Within the continental United States (CONUS) the relationship between the Military Sealift Command, Pacific (MSCPAC) and WAMTMC is very close. In order to get its cargo aboard break bulk or container vessels, WAMTMC notifies MSCPAC of the amount of space required, the number of containers needed by the shipper and the size of the containers. MSCPAC books the space aboard a vessel and notifies WAMTMC of the vessel sailing date, lift date for the containers and the number of containers booked. This procedure is carried out whether the shipper is a vendor or WAMTMC is the shipper.

G. MTMC MANAGEMENT INFORMATION SYSTEMS

MTMC employs two management information systems in order to control the flow of cargo within CONUS that will be eventually shipped to overseas commands. Both systems utilize a Burroughs 5500 computer. The two systems are the Mechanized Export Traffic System (METS) and the Surface Export Cargo System (SURS).

METS monitors the DoD cargo flow from its origination at the consignor's warehouse until its arrival at a state-side Port of Embarkation, i.e., one of WAMTMC's three ocean terminals. The consignor, which may be a commercial vendor or a military depot, thus provides the basic input into the system. This input includes shipment data, commodity

information, transportation data, destination, etc. Improperly formatted documentation is frequently received from the commercial vendors requiring the correction of these errors by manual methods.

Once cargo is within one of the three west coast ocean terminals, it falls under SURS, or SURS/CARDPAC. A CARDPAC is a set of eight IBM cards containing various shipping data. These cards have been punched by terminal personnel with data obtained from METS and any additional information that may be needed from shipping forms.

The CARDPAC; the Expected Receipt List (ERL), a list of the cargo expected in a particular shipment; and the applicable source document, e.g., a Government Bill of Lading (GBL), Commercial Bill of Lading (CBL), Dray Tag, or Transportation Control and Movement Document (TCMD) are forwarded to the terminal's cargo receiving area. As the cargo is unloaded a check is made against information contained on the CARDPAC and corrections are made if necessary. The CARDPAC is then attached to the shipment and will be utilized to monitor its flow through the terminal facilities.

In summary, by using the METS and SURS management information systems, WAMTMC is able to monitor the flow of cargo into and within its terminal facilities. Management reports generated by the system and statistical analyses based on the information provided by the system are only as good as the data going into it.

H. CARGO CLASSIFICATION

There are two types of cargo passing through the Container Stuffing Station: (1) release unit (RU); and (2) less than release unit (LRU).

Shipments in excess of 10,000 pounds and special category cargo, such as classified cargo, are classified as release unit material. Under DoD Regulation 4500.32-R, Military Transportation and Movement Procedures (MILSTAMP), release unit material requires positive export traffic release.

Consignors having break bulk or containerizable cargo that fall into RU classification must request and receive clearance to move that material before it can be shipped. WAMTMC, Export Control Division, serves as the clearance authority for RU material for the fourteen Western states.

This thesis is not concerned with break bulk or source stuffed cargo. Therefore, this paper will not go into a detailed description of the booking procedure except to mention that it is accomplished through the coordinated efforts of MSCPAC, WAMTMC, the shipper and the commercial carrier.

It should be mentioned that if RU classified cargo is not of sufficient quantity to be source stuffed, it is shipped to the CFD for stuffing.

Eighty percent of the shipments passing through MOTBA are of the LRU classification. LRU material does not require positive release into the system. Therefore, there is an uncontrolled flow of cargo coming into the Container

Freight Division. This results in a very difficult booking problem for the Container Freight Division, MOTBA, WAMTMC and MSCPAC. It is the forecast of this uncontrolled cargo flow to which this thesis addresses itself.

Figure 3 represents the cargo cycle to be considered. The procedures at each step are as follows [Ref. 15]:

1) A DoD overseas command makes a request for goods by requisition. The specific requestor is the user of these goods and the ultimate consignee. The requisition is to be filled by the shipper (consignor) who may be a commercial vendor or a military depot.

2) Material that is classified as less than release unit is shipped by the consignor directly to the Container Freight Division at MOTBA.

3) Under Military Traffic Management Regulation, container requirements are offered to WAMTMC by MOTBA.

4) A request for booking is then submitted to MSCPAC.

5) MSCPAC then books space aboard ocean carrier.

6) Once booking aboard the vessel is made, the related information is forwarded to WAMTMC.

7) The Container Freight Division at MOTBA receives the booking data from WAMTMC.

8) The Container Freight Division communicates directly with the ocean carrier to arrange for spotting and pick-up of containers.

9) Once containers have been stuffed at the CSS, they are delivered directly to the ocean carrier's container yard. From this point shipment from POE to POD is made.

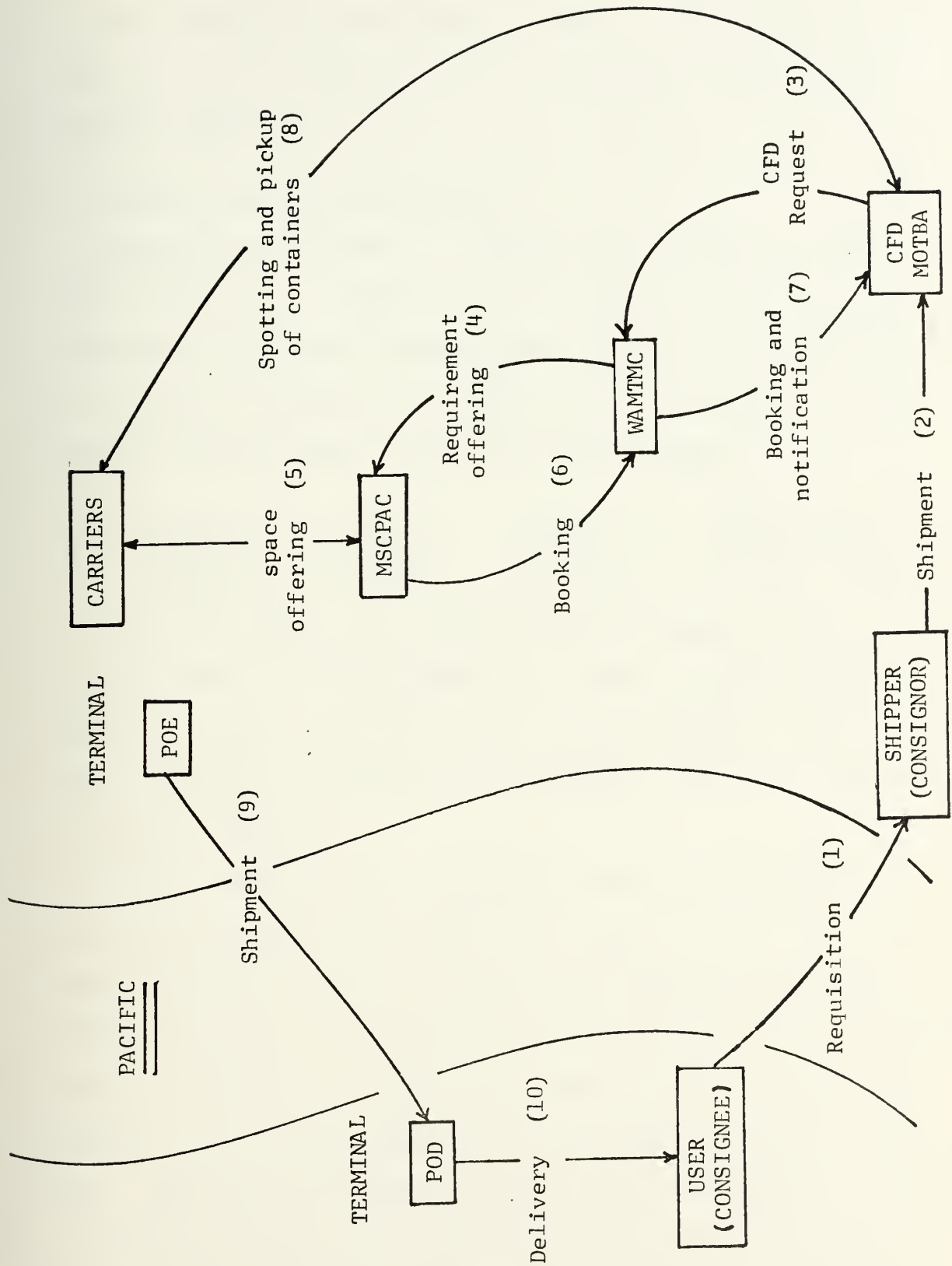


Figure 3: Supply and Transportation Cycle for Containers [Ref. 15].

10) Delivery of material is made to the consignee by either the ocean carrier or by arrangements made by the overseas command.

I. CURRENT BOOKING PROCEDURES

As previously stated, a request for booking is made twenty-one days in advance and is based on a forecast of the volume of cargo in measurement tons that is expected to be on-hand at the time the vans are to be stuffed. An offering is made based on the following formula:

$$\text{Booking Offering} = (\text{Cargo-on-hand}) - (\text{Cargo Booked}) + (\text{Forecasted Cargo Receipts}).$$

The CSS computes the previous three weeks average weekly receipts and uses this figure as a basis for forecasting the volume of cargo arriving at the facility between the date of offering and the stuffing of containers. Figure 3 illustrates the present method.

Figure 4 depicts the situation where a particular POD has 100 measurement tons (MT's) of cargo on the floor on Julian calendar day 70. To keep the computations simple, 250 MT's of cargo will represent the average weekly receipts for this POD for the past three weeks (15 days, since only weekdays are included) giving average daily receipts of 50 MT's. Container space has already been booked aboard three vessels during the 21- day period under consideration. The cutoff dates have been made for days 77, 79 and 84 for 360, 80 and 120 MT's respectively. Using the past three weeks average receipts as the basis of the forecast, there

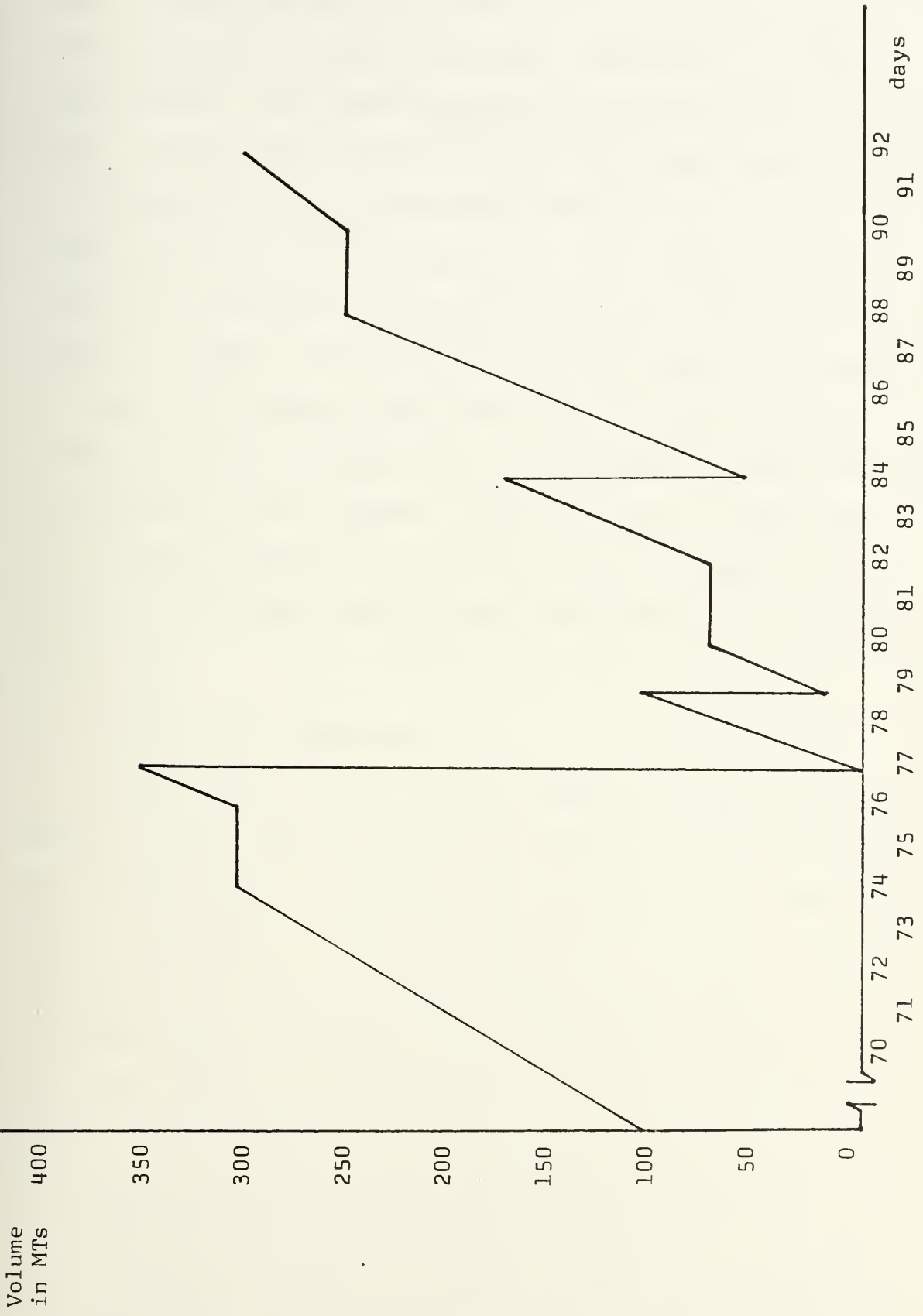


Figure 4: Booking Procedure

will be 360 MT's on-hand on day 77. The two-day period where no cargo accumulation occurs represents a Saturday and a Sunday. The five working days will accumulate 250 MT's. Since space for 360 MT's has been previously booked, all cargo on the floor for this POD will be stuffed. Two days later there will be 100 MT's on the floor but 20 MT's will not be stuffed. On day 84 only 120 of the 170 MT's will be stuffed. By day 91, the day for which the forecast is made, the forecast says there will be 300 MT's on the floor for this particular POD. The number of vans requested will depend on the average cube utilization for the POD. If the POD's average is 50 MT's then an offering for six vans will be made on day 70 to be available for stuffing on day 91.

J. CANCELLATION PROCEDURE

Cancellation of space booked aboard a carrier must be made no later than "a reasonable length of time" prior to the cutoff date according to MSC's Container Agreement and Rate Guide, RG8. If cancellation cannot be made within this time and if the carrier cannot utilize this space, then the government may be charged for the space even though it was not used. The present policy at WAMTMC is to cancel no later than five days prior to cutoff.

K. OPERATIONAL RESTRICTIONS AND REQUIREMENTS

It should be noted that there are other operational restrictions and requirements that affect stuffing and booking procedures, although a thorough understanding of them is not

essential to this work. Briefly they are: 1) a first-in-first-out (FIFO) cargo stuffing procedure requiring a minimum average FIFO performance of 80% for each POD, 2) shipment priorities that are exceptions to the FIFO procedure, 3) a requirement for the timely handling of certain goods such as household effects, 4) a requirement for a monthly cube utilization average of 75% with no less than 50% cube utilization to ensure that container utilization is more economical than break bulk shipping, 5) a restriction on cargo mixing such as Military Assistance Program (MAP) cargo not being permitted to be mixed with any other type of cargo, 6) the requirement of contracting the low cost carrier if there is more than one that can provide the required service, and 7) a ceiling of 4,000 measurement tons on the floor at any one time.

III. STUDY OBJECTIVES AND PROCEDURES

A. STUDY OBJECTIVES

The essence of this study is to observe the flow of cargo into the Container Freight Division at MOTBA and attempt to forecast by statistical and analytical techniques the expected cargo inputs at some future point in time. The forecast is of the volume of containerizable cargo passing through the CFD destined for a particular POD. Break bulk cargo volume and source stuffed vans are not considered in this analysis.

The necessity for such a forecast evolves from the fact that the Military Sealift Command must book container space aboard vessels as much as three weeks in advance of lift. Because of the demand for container shipping in recent years, commercial carriers are able to make this demand on their customers. It remains to be seen whether a shift in the supply and demand factors will alter this requirement to any significant extent.

Although forecasting and forecasting models are generally associated with inventory and production control, the same general principles apply to the situation at MOTBA. Essentially, the situation is one of demand -- the demand by overseas commands for material support. In this respect the forecasting problem can then be broken down into components of that demand. Examples of these components are average demand, trend effects, seasonal effects, and noise or random effects. By recognizing these components one can then construct statistical models to deal with them.

Accurate forecasting may have an influence on some of the performance variables that the container booking system generates. These are frequency of cancellations due to overbooking, age of cargo at stuff, cube utilization, and total volume of cargo on the floor.

In forecasting, the past is projected into the future. A good forecasting model should provide information feedback accurately and quickly so that the manager can make the necessary and appropriate adjustments. It should provide a means of reflecting sudden shifts caused by policy changes within the system or uncontrollable exogenous factors which may also influence the system. A forecast that is based on out-dated information will not be beneficial to a manager who must book container space three weeks in advance.

A forecast is only as good as the data it uses. In this thesis it is assumed that the historical cargo flow data used to evaluate the forecasting methods is accurate. Data totals obtained from the computer tapes were verified against the totals that were manually computed at MOTBA.

B. PROCEDURES

As stated previously the system variable that this thesis addresses is the volume of containerizable cargo for a POD flowing into the Container Freight Division at MOTBA. Although there are weight restrictions to consider, these restrictions have not been significant factors in the booking procedure.

The data used throughout this thesis was taken from actual operations at the Container Stuffing Station. The data covers an 18-month period dating from 1 January 1973 to 30 June 1974. This period generated an enormous volume of data which reflected the magnitude of the container stuffing operations at MOTBA.

In order to handle this volume of information the analysis was done in four separate phases. These were:

- 1) a distribution audit in order to identify the variables needed in the analysis,
- 2) the grouping of data in a more usable format,
- 3) a test for serial correlation in the data, and
- 4) the application of various forecasting techniques and their evaluation.

In performing the distribution audit some of the computer programs from the McCarthy and Carter thesis were utilized. Only slight modifications to these programs were needed to manipulate the enormous volume of data generated by the eighteen months of operations. The audit identified the number of shipments and the volume of these shipments. From this information one could identify major Ports of Debarkation, thus narrowing the scope of the problem.

In order to arrange the data into a more usable format a number of short computer programs were written. These programs grouped the data from daily to weekly totals in the aggregate as well as POD levels.

Since this work dealt with time-series analysis it was reasonable to test the data for serial correlation in order

to limit the range of potential forecasting methods. A computer program was utilized to calculate the statistical information needed to evaluate the various PODs.

Several computer programs were then used to apply various forecasting techniques to the data. The simplest techniques were applied first. In some cases these initial techniques were expanded to take into consideration the components of demand previously mentioned. The various forecasts were then evaluated based on the difference between the forecasted and actual volume.

All the computer programs used in the data analysis were written in the FORTRAN IV computer language. These programs were run on the IBM 360/67 computer at the W. R. Church Computer Center, Naval Postgraduate School, Monterey, California.

IV. DATA ANALYSIS

A. DISTRIBUTION AUDIT

Raw data was taken from a set of 19 computer tapes supplied by WAMTMC and was combined with existing data from previous research work to form a set of data covering 18 months. The period covered was Quarters III and IV of FY '73 and all four quarters of FY '74. Computer programs were used to extract the pertinent information from the tapes, combine it with existing data and place the aggregate information in alphabetical order by POD and consignee in a data file.

Computer Program Two of the McCarthy and Carter thesis was used to delineate the data for further analysis. This program determined the number of shipments, the total volume, the average volume, the standard deviation of the volume, the total weight, the standard deviation of the weight, the average density and the standard deviation of the density for each POD. The program also grouped each POD's shipments into intervals of volume, weight and density.

The next procedure entailed the examination of the gross weekly totals of shipments and volume of cargo arriving at the container stuffing station during the 18-month period. The following information was obtained:

SHIPMENTS

Quarters III & IV, FY '73	111,463 shipments
FY '74	124,592 shipments
18-month Totals	236,055 shipments

VOLUME

Quarters III & IV, FY '73	8,398,931 cubic feet
FY '74	10,070,724 cubic feet
18-month Totals	18,469,655 cubic feet

There was obviously a tremendous amount of activity at MOTBA during the second half of FY '73. Over 47% of the total shipments and 45% of the total volume for the 18-month period occurred during the first six months of the data set.

It was concluded that residual Vietnam conflict effects were responsible for generating this high volume of activity during the first six months of the 18-month period and that it did not represent the present and the expected future flow of cargo at MOTBA. Therefore, it was decided to use only the data for FY '74.

The audit was run a second time using only FY '74 data. During that period 157 PODs and 3,356 consignees were identified as having received shipments during this period. These PODs and consignees accounted for 124,592 shipments with a total volume of 10,070,724 cubic feet as previously stated. This was an average weekly total of 2,396 shipments with an average weekly volume of 193,668 cubic feet (or 4,842 measurement tons). Total weight for the period was 176,213,333 pounds.

In reviewing the yearly gross totals for the 157 PODs, it was obvious that 10% of these dominated the activity at MOTBA. Sixteen PODs were identified as being the most active in terms of volume of cargo arriving at the container stuffing station during the period. The cutoff point was

arbitrarily chosen at 100,000 cubic feet of volume per year. As a result the least active of the 16 major PODs averaged a volume input of 2,041.35 cubic feet per week (or approximately 51 measurement tons). The number of shipments for these major ports totalled 115,732 or 92.89% of all shipments for the period. Their volume total of 9,370,693 cubic feet was 93.05% of the total volume.

Table I, Appendix A, shows the weekly gross totals of shipments, volume and weight arriving at the CSS in the second half of FY '73. The totals for FY '74 appear in Table II. Table III, Appendix A, shows the data summary of the distribution audit. Tabular data for the 16 major PODs is presented in Table IV. Table V lists the activities of the major PODs by shipments, volume and weight.

The computer output of the intervals of weight into which each of the shipments fell provided a look at the portion of the release unit shipments arriving into the system. If the number of release units were significantly large, it may be possible to forecast with greater accuracy the volume of cargo expected to arrive during a specified period.

There were 1,900 shipments of ten thousand pounds or more during FY '74 using only data generated by the 16 major PODs. These shipments should have been classified as release unit shipments and it is assumed that they were. They represented 1.64% of the shipment totals for the major ports.

It was concluded that the amount of release unit shipments arriving at the container stuffing station was insignificant in view of these figures. Furthermore, operations at

MOTBA indicate that the expected arrival date of RU cargo was an unreliable item. Therefore, RU cargo was considered part of the uncontrolled cargo flow and grouped with LRU data for the purpose of this work. Table VI, Appendix A, shows the number of RU shipments classified because of weight for each of the major PODs.

It should be noted that no attempt was made to determine the number of shipments classified as RU for reasons other than weight (i.e., classified material). It was assumed that the volume of this cargo was of insignificant proportion when compared to the total yearly volume.

In summary, the distribution audit provided a means of taking raw data and arranging it into a meaningful and useful format. It permitted the identification of the most active ports of debarkation which then became the focal point for further analysis. The grouping of the data into weekly intervals by POD indicated the tremendous volume fluctuations that occurred throughout the period and the apparent complexities that arise when attempting to forecast future volume flow.

Up to this point, only the simple computer manipulation of data had been accomplished through the distribution audit. With this phase completed, there were still many questions to be answered. What type of data had been generated? Was there any correlation in the volume flow from week to week?

The above questions are answered in the following section which begins the statistical analysis of the data. The answers then provide statistical justification for applying

certain forecasting techniques which are covered in section C of this chapter.

B. SERIAL CORRELATION TEST

The flow of uncontrolled cargo volume into the Container Freight Division at MOTBA is time-series data. It is not uncommon for future observations in real time-series data to be dependent upon current observations. This dependence may be measured by analysis of the consecutive disturbances around a simple least-square-regression line. If these disturbances are found to be correlated from one observation to the next, and thus not random, serial correlation is said to be present. If the presence of serial correlation can be properly identified it can result in a more efficient estimation process in comparison to simple least-squares estimators. Such a process would give more weight to recent data for creating predictions of the values of future observations.

Johnston [Ref. 9] lists three main consequences that result from applying straightforward least-squares formulas directly to observations that contain serially correlated disturbances. They are:

- 1) The sampling variances of the intercept and the slope coefficient may be unnecessarily large in comparison to those obtained by other methods.

- 2) The usual least-squares formulas for the sampling variances of the regression coefficients are no longer valid since a serious underestimate of the variance is likely to occur.

3) The sampling variances of the prediction will be unnecessarily large.

1. The Durbin-Watson d-Statistic

When making forecasts using time-series data it would be a serious error to assume serial independence of the disturbance term. In order to avoid such an error, the Durbin-Watson d-Statistic [Ref. 6] provided a suitable test for the presence of serially correlated disturbances. The Durbin-Watson d-Statistic is defined by

$$d = \frac{\sum_{t=2}^n (Z_t - Z_{t-1})^2}{\sum_{t=1}^n (Z_t)^2}$$

where $Z_t (t=1,2,\dots,n)$ denotes the residuals from a fitted-least-squares regression. To determine positive serial correlation the observed value of d is compared against lower and upper bounds of d_L and d_U that are tabulated for various values of n (the number of observations) and k (the number of explanatory variables). The d -statistic for negative serial correlation is calculated by taking $4 - d$. This figure is also compared with d_L and d_U . Since the sign of the serial correlation was unknown, two-sided tests were conducted by combining single-tail tests. The test has four possible outcomes: (1) positive serial correlation of the data; (2) negative serial correlation of the data; (3) inconclusive evidence of serial correlation with further observations being ideally required; or (4) no presence of

serial correlation (which implies that the disturbances are random).

The calculations were made using three different intervals. The first interval used weekly data resulting in 52 observations. The second interval used biweekly totals beginning with the observation for the first two weeks of FY '74. The total number of observations in this set was 26. Biweekly totals beginning with the observation of the second and third weeks of FY '74 (i.e., ignoring the first week's volume total) was used for the third interval. Thus there were only 25 observations resulting from this grouping scheme.

The following example may help to clarify the above procedure. Given that the weekly volume input for POD, BA3, for the first seven weeks of FY '74 is 10, 20, 30, 40, 50, 60 and 70 cubic feet respectively, the first seven observations for the weekly interval data set correspond accordingly. The first three observations for the first biweekly data set will be 30, 70 and 110 cubic feet. However, the first three observations for the second biweekly data set will be 50, 90 and 130 cubic feet.

The d-statistic test was implemented through Computer Program One. In addition to displaying the results of the calculations, the program displays the meaning of the d-statistic (i.e., positive, negative, inconclusive or none). Computer Output One at the end of this thesis is a sample of the printout for Computer Program One.

2. Results of Serial Correlation Test

While the Durbin-Watson d-Statistic was calculated for all 157 PODs, the d-statistic for the 16 most active PODs was the focal point for the analysis.

The results of the test for the weekly interval data set having 52 observations for each POD indicated positive serial correlation in the weekly volume inputs for nine PODs. The test was inclusive for four PODs and indicated no serial correlation for three others. There were no PODs with negative serial correlation. In fact, there was no indication of negative serial correlation under any of the circumstances tested for all 157 PODs. The following table shows the test results using only the 16 major PODs. The test was conducted at a level of significance of 0.05.

<u>Week per Interval</u>	<u>Week Started</u>	<u>Positive</u>	<u>Results</u>			<u>No Correlation</u>
			<u>Negative</u>	<u>Incon</u>		
1	1	9	0	4	3	
2	1	5	0	5	6	
2	2	7	0	5	4	

Table VII gives the d-statistic results for each POD for the three intervals tested.

Given the results of the d-statistic tests it was then decided to test for the aggregate presence of serial correlation in the data for the 16 major PODs. The null hypothesis for the test was

$$H_0: \rho_1 = \rho_2 = \dots = \rho_{16} = 0$$

where ρ_1, \dots, ρ_{16} symbolically represents the serial correlation coefficients for the 16 major PODs. The alternate hypothesis was

$$H_1: \text{ not all } \rho\text{'s} = 0.$$

This hypothesis is, in essence, testing the plausibility that the individual cases indicating positive serial correlation were Type I errors, i.e., a rejection of the null hypothesis, $\rho_i = 0$, when it was true. This was formulated as a Bernoulli process with the probability of success (the indication of positive serial correlation) equal to the level of significance for the d-statistic test (0.05).

Since a Bernoulli process was involved, the binomial distribution function was applied. Letting the probability of success, p , equal 0.05; the number of trials, n , equal to 16; and the specific number of successes, r , equal to 5, 7 and 9 respectively, the decision rule was

$$\text{Accept } H_0 \text{ if } P(R \geq r | n, p) > 0.05$$

$$\text{Reject } H_0 \text{ if } P(R \geq r | n, p) < 0.05$$

where R equals the unknown number of successes.

Using cumulative probability distribution tables the following results were obtained:

$$P(R \geq 5 | 16, 0.05) = 0.0009$$

$$P(R \geq 7 | 16, 0.05) = 0.0001$$

$$P(R \geq 9 | 16, 0.05) < 0.0001.$$

Based on these results the null hypothesis was rejected and it was assumed that significant serial correlation

surely existed somewhere in the data. Therefore, there was justification for using methods other than ordinary-least-squares regression to forecast the volume of cargo arriving at the Container Freight Division at MOTBA.

C. FORECASTING METHODS

The results of the Durbin-Watson d-Statistic indicated the presence of serial correlation and thus the serial dependence of the observations. It showed that the disturbances around an ordinary-least-squares regression line would not fall equally on each side of the line. As the disturbances tended to fall more on one side of the line than the other, this implied that the most recent disturbance was the best predictor of the subsequent disturbance. Also, by implication, the best predictor of the next observation is the most recent observation or observations. This supplied justification for the application of forecasting methods other than ordinary-least-squares to place more emphasis on recent data rather than the minimization of the squared residual term. While there were a number of methods from which to choose, the methods used in this work were chosen because of their relevancy to the problem and for their ease of calculation.

This section looks at: the moving average method that is presently being used at MOTBA; the exponentially weighted average method; the exponentially weighted average method with adjustment for trend; and an adaptive response rate technique applied to the exponentially weighted average method.

These methods were evaluated using mean absolute deviation (MAD) and mean deviation squared (MDS) as the criteria for goodness. By computing the mean of the deviations it was possible to compare the various forecasting methods when they resulted in differing numbers of forecasts generated during the period.

In addition, MAD and MDS were computed for one-, two- and three-week time horizons. For the one-week time horizon the forecast was subtracted from the actual input volume on a week by week basis. For the two-(three-)week time horizon the latest forecast was multiplied by two (three) and subtracted from the actual input volume for the two (three) weeks covered by the forecast. This was done on a week by week basis.

The following example may help to clarify time horizon calculations. Say that the forecast for week 20 is 1,000 cubic feet. If a three-week time horizon is being used, the forecast will be 3,000 cubic feet for weeks 20, 21 and 22. If the actual input volumes turn out to be 900; 1,100 and 1,200 cubic feet respectively, the absolute deviation for the forecast is then 200 cubic feet (or $900 + 1,000 + 1,200 - 3,000$). Week 21 will result in a new forecast for weeks 21, 22 and 23. The forecast for week 21 is multiplied by three and subtracted from the actual input volumes for weeks 21, 22 and 23 to determine the absolute deviation for that particular forecast. Thus, for each forecast there is an absolute deviation that is computed.

What, then, was the purpose for using time horizons? One reason was the requirement for booking container space three weeks in advance and thus projecting a one-week forecast over a period greater than one week. One-, two- and three-week horizons were used to make comparisons of any effects that may be caused by changes in the booking requirements. It was also anticipated that an increase in the time horizon may have some effect on the results of the various forecasting methods due to a dampening effect on data with large fluctuations. This dampening effect is explained later.

It should also be noted that comparisons among the various forecasting methods were only made within a given time horizon.

Tables VIII and IX, Appendix A, show the MADs and MDSs generated by all of the forecasting methods used in this analysis.

1. Moving Average Method

As previously explained, the CSS at MOTBA computes the previous three weeks average receipts in order to forecast the input volume that will be on hand in 21 days. The offerings for bookings that are made depend on three factors: 1) the volume of cargo on hand; 2) the volume of cargo booked; and 3) the forecasted volume.

The three-week moving average is nothing more than a linear average. This average, multiplied by three is then used to forecast the volume receipts for the next three

weeks. In this method equal weight is given to each of the past three weekly volume totals.

In order to evaluate the moving average method the MADs and MDSs were calculated for one-week to ten-week moving averages for the 16 PODs. In addition, the aggregate MAD and MDS for each POD were calculated for one- to ten-week moving averages. In other words, a specific moving average (from one to ten weeks) was applied to the volume inputs for each POD. The MAD and MDS for each POD were calculated and then summed to get the aggregate. The same calculations were made for two- and three-week time horizons.

Computer Program Two was utilized to obtain the calculations for the analysis of the moving average method. Computer Output Two shows a portion of the output that was generated by the program.

a. Data Analysis of the Moving Average Method

In 13 of 16 cases a moving average other than the three-week moving average provided a better forecast when MAD was the criterion of goodness. When using MDS as the criterion, the result was 15 of 16 cases. The time intervals that provided the best forecast will be called the "optimal moving average."

These evaluations were made using a one-week time horizon. Similar results were obtained using two- and three-week time horizons except that the optimal time interval for the moving average was not the same in each case.

It was noted that in some cases the selection of the goodness criterion determined the optimal interval for

the moving average. This was the case for six PODs using a one-week time horizon and was true to a greater or lesser extent for the two- and three-week time horizons.

The decrease in the MAD when a moving average other than a three-week moving average was optimal, varied from 4.5% to 18.5%. Similar reductions in MAD and MDS occurred when the other time horizons were used.

The optimal time interval for a moving average that applied to all PODs was seven, ten and ten weeks for one-, two- and three-week time horizons, respectively, with MAD as the criterion. The same time intervals held true with MDS as the criterion.

It was noted that the number of forecasts decreased as the time interval for the moving averages increased. For example, in a three-week moving average, the first three weeks are averaged to make a forecast for week four. Thus, there were only 49 forecasts made for the period. For a ten-week moving average there were only 42 forecasts. The use of two- and three-week time horizons resulted in even fewer forecasts. Comparison among the various moving averages for a specific time horizon was possible since mean absolute deviation and mean deviation squared were used as the criteria for goodness.

As the time interval for the moving average increased, the greater was the chance for large fluctuations in the data to be dampened by the initial forecast. For example, the volume inputs for the first six weeks of FY '74 for TAI were 2,611; 4,307; 1,079; 3,360; 6,765 and

2,429 cubic feet, respectively. These fluctuations were dampened when moving averages greater than three weeks were applied to the data (with a five-week average being optimal). This dampening effect stressed the fact that a three-week moving average placed more emphasis on recent data. Longer time intervals placed less emphasis on recent data and considered older data as well.

It was also noted that the MAD and MDS decreased as the time horizon increased. The reason was that the two- and three-week time horizons also tended to cancel the volume fluctuations. A look, again, at Figure 1 shows the very large volume fluctuations that occur in the POD data and how it is possible for the dampening effect to take place.

2. Exponentially Weighted Average Method

In lieu of the results of the serial correlation test, a viable alternative to the moving average method is the exponentially weighted average (EWA). In its simplest form an EWA is based on a period by period adjustment of the most recent forecasted average by adding or subtracting a fraction of the difference between the actual volume in the current period and the latest forecasted average volume. It differs from the moving average in that the weight given the most recent observation can be varied while also giving consideration to all past data. EWA is represented by

$$\bar{F}_t = \alpha V_t + (1 - \alpha) \bar{F}_{t-1}$$

where \bar{F}_t is the forecast average, V_t is the actual input volume and α is the exponential smoothing constant which must be between zero and one. The forecast for the next period F_{t+1}^* can be taken directly from the computed value of \bar{F}_t . This can be justified because trends and seasonal adjustments are not accounted for in the model [Ref. 7].

The exponentially weighted average method is also known as the exponential smoothing method. Both names are used in this thesis.

The calculations for the EWA method were implemented by Computer Program Three. The MAD and MDS for each POD were calculated for α -levels between -0.10 and +1.00 in increments of 0.01. In addition the MAD and MDS were computed for α -levels that were applied to all 16 PODs. In other words a specific α -level was applied to data for each POD. The MAD and MDS for each POD were calculated and then summed to obtain an aggregate total. The α -levels which generated the smallest MAD and MDS are referred to as the "optimal α -levels for aggregate data." It should be noted that the optimal α -levels for aggregate data may differ depending on the criterion of goodness.

A canned computer subroutine, SUBROUTINE OSPLOT, available at the computer center, was used to plot the α -levels versus the MAD for each POD. The plot displayed how the MAD reacted to various levels of α . Thus it was possible to visually determine the optimal α -level for aggregate data with MAD as the criterion of goodness.

Computer Output Three-Two shows the MADs and MDSs calculated for various α -levels. Computer Output Three-One is a sample of the OSPLIT for four of the PODs.

a. Data Analysis of EWA Method

With MAD as the criterion for goodness, the EWA method resulted in a decrease in MAD in 14 of 16 cases when compared to the three-week moving average. The decrease ranged from 4.9% for RJ3 to 12.4% for XJ1. However, when EWA was compared to the optimal moving averages for the individual PODs it produced a smaller MAD in only 4 of 16 cases. The α -levels varied from 0.04 to 0.60 for the 16 PODs.

The optimal α -level for aggregate MAD data was 0.36. The aggregate MAD for the EWA method was 59,387 cubic feet as compared to 60,172 cubic feet for the three-week moving average and 59,209 cubic feet for the optimal moving average.

The preceding analysis was made from calculations using a one-week time horizon. Similar results were obtained using two- and three-week horizons. It is interesting to note that there were changes in the α -levels for most PODs depending on the time horizon. One POD (UM4) produced negative α -levels (-0.02 and -0.01) for two- and three-week time horizons, respectively. The optimal α -levels for aggregate data were 0.35 for the two-week horizon and 0.33 for the three-week horizon. As was the case with the moving average method, the aggregate MADs decreased as the time horizons increased due to the dampening of the fluctuations.

With MDS as the criterion for goodness the EWA method resulted in a decrease in MDS in 12 of 16 cases when compared to the three-week moving averages. When compared to the optimal moving average, there was a decrease in only 5 of 16 cases. In each case the optimal α -level for MDS was different from the optimal level for MAD; although the optimal α -level for aggregate data was approximately equal for the MDS (0.37) and the MAD (0.36). The aggregate MDS for the EWA method was less than the MDS for the three-week moving average but greater than the MDS for the optimal moving average.

A one-week time horizon was used in the above analysis for MDS. As was the case with the MAD analysis of individual PODs, two- and three-week time horizons generated similar results. However, for a two-week time horizon of aggregate data, EWA generated a slightly smaller MDS than that generated by the optimal moving average. This was not the case for the three-week time horizon, however.

The way in which the EWA method was applied resulted in no forecast deviations being computed until the third week. This resulted in some smoothing of the data but not as much smoothing as occurred with moving averages with intervals greater than three weeks. When applying the EWA method to data with large fluctuations at the beginning of the year, there was a lag in the forecast until these fluctuations were dampened over time. This was the apparent reason for the seven-week moving average being a better

forecaster than the EWA for a one-week time horizon and a ten-week moving average being better for a two- and three-week time horizon.

In summary, the EWA method provided a means of emphasizing past data as well as placing some significance on the most recent data by the use of the smoothing constant. The EWA method provided a better forecast than the three-week moving average; however, the decrease in the MAD for aggregate data was only 2.2%. For individual PODs this decrease was as high as 18%, but for other PODs there was an increase in the MAD when EWA was used.

3. Exponentially Weighted Average Method with Trend Adjustment

Neither the moving average or the EWA took into consideration any adjustment for trends that may exist in the data. Also, the slopes of the least-squares-regression line for some PODs used in the d-statistic calculations gave an indication of the possibility of trend effects in the data. Therefore, the EWA was modified to take into account the adjustment for trend.

The difference between the volume forecast averages from week to week is the apparent trend. Exponential smoothing can be applied to this trend just as it was applied to the forecast average. This trend adjustment is represented by

$$\bar{T}_t = \alpha(\bar{F}_t - \bar{F}_{t-1}) + (1 - \alpha) \bar{T}_{t-1}.$$

By combining this trend adjustment with the new forecast average, the forecast for the next period is then

$$\bar{F}_{t+1}^* = V_t + (1 - \alpha) \bar{F}_{t-1} + \frac{1}{\alpha} \bar{T}_{t-1}$$

or

$$\bar{F}_{t+1}^* = \bar{F}_t + \frac{1}{\alpha} \bar{T}_t$$

where \bar{F}_{t+1}^* is the forecast for the exponentially weighted average with trend adjustment (EWA-TA) [Ref. 7].

Computer Program Four was used to make the statistical calculations for the EWA-TA. Except for the trend adjustment, the computational procedures were the same as those for the EWA method. Once again, SUBROUTINE OSPLOT was used to plot α -levels versus MAD for each POD.

a. Data Analysis of EWA-TA

Using a one-week time horizon and MAD as the criterion, a decrease in MAD resulted in only 3 of 16 cases when comparing EWA-TA to EWA. Only in the case of RG1 was there any significant change (an 8% decrease). However, this POD was an exception to the rule of fluctuating volume inputs. Its weekly volume inputs toward the last half of the year had remained within a relatively small range. In only one case did EWA-TA provide a better forecast than any of the methods previously discussed. However, the improvement was minimal. In half the cases the difference in MADs between EWA-TA and EWA was less than 50 cubic feet. Also, the α -level dropped significantly in all 16 cases. The optimal α -level for aggregate data was 0.16; however, the MAD was greater by 1,904 cubic feet.

With MDS as the criterion for goodness the results were similar. Improvement on the EWA method occurred in only two cases. In most cases the α -levels were different from those with MAD; however, the optimal α -level for aggregate data changed by only 0.01 to 0.17. The aggregate MDS was the largest of all the methods applied thus far. This was true for all time horizons.

Very few changes occurred when two- and three-week time horizons were applied. Once again, UM4 produced negative α -levels. The optimum α -levels for aggregate data did not change significantly. The aggregate MAD and MDS decreased in the same proportion as the aggregate totals for the other methods.

In summary, the exponentially weighted average method with trend adjustments did not provide an improved forecast over the moving average method or the exponentially weighted method without trend adjustments. Apparently there was no definite trend in the volume inputs for the PODs. It is doubtful that the method can be effective when applied to data covering only a one year period.

4. Exponentially Weighted Average with an Adaptive Response Rate

Because of the large volume fluctuations in the data, the application of an adaptive response rate (ARR) provided a plausible alternative to a simple exponentially weighted average. The ARR provides an automatic means of detecting sudden volume changes through the use of a tracking signal. Trigg and Leach [Ref. 18] define the tracking signal as

$$\text{Tracking Signal} = \frac{\text{Smoothed Error}}{\text{Smoothed Absolute Error}}$$

where the error is the difference between the forecasted volume and the actual volume inputs in each period. The error was smoothed by choosing a value for gamma, γ , between -1 and +1 such that

$$\text{New Smoothed Error} = (1-\gamma) \text{ old smoothed error} + \gamma \text{ error,}$$

$$\begin{aligned} \text{New Smoothed Absolute} \\ \text{Error} \end{aligned} = (1-\gamma) \text{ old smoothed absolute error} \\ + \gamma \text{ absolute error.}$$

The tracking signal was then applied to the EWA methods without trend adjustment by letting the smoothing constant equal the absolute value of the tracking signal. Thus, it appeared that ARR would provide a rapid response to large volume changes whereas the constant model would lag behind these sudden changes.

The adaptive response rate was also applied to the exponentially weighted average with trend adjustment. It resulted in very large deviations because of the conflict between the trend adjustment and the response rate. They were apparently working against each other; and therefore, this method will be ignored in this paper.

MADs and MDSs for the 16 major PODs were calculated for γ -levels between -1.00 and +1.00 in increments of 0.01. Optimal γ -levels for aggregate data were also computed. These calculations were implemented by Computer Program

Five. Plots of γ -levels versus MAD were made through the use of the special subroutine

a. Data Analysis of EWA with ARR

With a one-week time horizon and MAD as the criterion, the ARR resulted in the smallest MAD in 6 of 16 cases when compared to all other methods previously discussed. The reduction in MAD was less than 5% in five of these cases. The optimal γ -level for aggregate data was -0.05 . The aggregate MAD at this level was smaller than the MADs for the three-week moving average and the EWA-TA; but it was larger than the MADs for the optimal moving average and the EWA method.

A two-week time horizon produced similar results on the individual POD as well as aggregate level. Individual POD results were similar with a three-week time horizon. For aggregate data only the optimal moving average resulted in a smaller MAD. However, the reduction was less than 1%, and for all practical purposes it was equal.

With a one-week time horizon and MDS as the criterion, the ARR produced a lower MDS in 5 of 16 PODs when compared to all other methods. Two- and three-week time horizons had similar results on the POD level. For aggregate data, the ARR was unable to generate an MDS smaller than any of the other methods for the three time horizons.

In summary, the ARR provided a more complicated approach to exponential smoothing than any of the other methods. On the individual POD level it provided a better forecast in some cases; yet, the improvement was minimal.

The time horizon and the criterion for goodness were significant factors in determining whether the ARR generated the better or best forecast.

While the purpose of the ARR was to respond more rapidly to large fluctuations in the data, it would be more appropriate to state that it was designed to respond to large fluctuations which resulted in a shift in the data. While there were large fluctuations in the data there were no apparent shifts in the data. Plots of the weekly volume inputs indicated that there were large fluctuations in the data, but that these fluctuations did not result in any significant shifts in the data.

5. Summary of Forecasting Methods

Four forecasting techniques were applied to the data: 1) the moving average method; 2) the exponentially weighted average method; 3) the exponentially weighted average method with trend adjustment; and 4) the exponentially weighted average method with an adaptive response rate. Past data was utilized to forecast future inputs in each of the methods. Each method provided a means of varying the amount of emphasis placed on the most recent data, forecast average, or error.

In order to evaluate the forecasting methods, the mean absolute deviation and mean deviation squared were calculated and used as the criterion of goodness. The mean of the deviations was used since each method resulted in a different number of forecasts being made for each period.

The MADs and MDSs that were generated by the various forecasting methods indicated the uniqueness of the volume inputs for each POD. The method providing the best forecast for a POD depended upon the criterion of goodness and the time horizon.

Tables VIII, IX, X and XI, Appendix A, are a presentation of the data that has been previously discussed. Table VIII gives the MAD of the various methods for the 16 major PODs in one-, two- and three-week time horizons. Table IX gives the MDS in the same format. Tables X and XI present the MAD and MDS for aggregate totals respectively.

From the data in these tables it can be seen that lower MADs and MDSs may result from increasing the time horizon. It has been suggested that the lower deviations were a mathematical result of the two- and three-week time horizons averaging the volume fluctuations. The reduction continued for each increase in the time horizon in 8 of 16 PODs. In only one case did a decrease not result from an increase in the time horizon from one to two or three weeks. In other words, in 15 of 16 cases there was a reduction in MAD when using a two- or three-week horizon.

The moving average method provided a means of dampening the initial large volume fluctuations in the data. Large volume fluctuations during the first quarter of FY '74 could be dampened by using a 10-week moving average. Thus, the first deviation was not computed until the eleventh week.

The other methods that were applied to the data began computing deviations as early as the third week. With large volume fluctuations at the beginning of the period it was possible that there was a lag in the forecast which initially resulted in large deviations. The plots of the weekly inputs showed that 8 of 16 PODs had large volume fluctuations at the beginning of the period. •

An overall view of the forecasting methods indicated that no one particular method dominated the others in terms of providing the best forecast on a POD or an aggregate level. The difference between the largest and smallest MAD was less than 100 cubic feet for one POD (UL7). For another POD (UM4) three different methods were optimal depending on the time horizon. These and other factors demonstrated the random flow of cargo arriving at the CSS.

6. Optimal Forecasting Method Selection

The results of the various forecasting techniques applied to the data provide a basis for the selection of an optimal method. Through the application of these techniques the following alternatives were available for forecasting the weekly volume inputs of the PODs:¹

(1) a three-week moving average,

(2) a moving average with an optimal time interval applied to all PODs.

¹See Tables X and XI, Appendix A.

(3) a moving average with the optimal interval for each POD applied to its weekly inputs (i.e., the time intervals vary among the PODs),

(4) an exponentially weighted average with the optimal α -level applied to all PODs,

(5) an exponentially weighted average with the optimal α -level for each POD applied to its weekly inputs (i.e., the α -level varies among the PODs),

(6) an exponentially weighted average with trend adjustment with the optimal α -level applied to all PODs,

(7) an exponentially weighted average with trend adjustments with the optimal α -level for each POD applied to its weekly inputs,

(8) an adaptive response rate with the optimal γ -level applied to all PODs,

(9) an adaptive response rate with the optimal γ -level for each POD applied to its weekly inputs.

The selection of the optimal method required an analysis of the methods used to calculate the goodness criterion and the application of Student's t-test in order to determine if the difference of the deviations among the methods were significantly different.

The results of the one to ten-week moving average indicated that a time interval greater than three weeks generated smaller deviations than the three-week moving average for 13 of 16 PODs. This ratio held true for both criterions and for all time horizons. Thus, if a moving

average is to be applied to the data, a time interval greater than three weeks is preferred.

There is one shortcoming in comparing the moving average method with the others. The first deviation for a moving average was not computed until the week following the time interval of the average while the deviations were computed beginning the third week for the other methods. Thus, the longer time intervals tended to have a greater initial smoothing of the forecasts while there was a lag in the smoothing for the other methods. This fact should be kept in mind when comparing the aggregate totals in Table X, Appendix A. Because of the manner in which the deviations were computed no comparisons were made between the optimal moving average and the other methods.

The exponentially weighted average offers an alternative to a moving average. Firstly, it did generate smaller MADs and MDSs than a three-week moving average. A simple t-test using MAD as the criterion and a one-week time horizon indicated that alternatives (4) and (5) are significantly different from alternative (1) at the 0.05 confidence level; and, therefore, (4) and (5) are preferred to (1). At the same confidence level, the t-test indicated that (4) and (5) are different; and, therefore, alternative (5) is preferred to (4). Not until a confidence level of 0.005 is used, can it be said that alternatives (4) and (5) are not significantly different.

The exponentially weighted average method with trend adjustment (alternatives (6) and (7)) generated aggregate

MADs and MDSs that were larger than those generated by the EWA without the trend adjustment. Based on this fact, alternatives (4) and (5) are preferred to alternatives (6) and (7).

The exponentially weighted average with an adaptive response rate (alternatives (8) and (9)) provided another alternative to the moving average method. For 6 of 16 PODs the ARR generated the smallest MAD for one- and two-week time horizons. On the aggregate level alternatives (8) and (9) generated slightly smaller MADs than did alternatives (4) and (5). A t-test indicated that alternatives (8) and (9) are different; and, therefore, (9) is preferred to (8). The test was conducted at the 0.05 confidence level.

With alternatives (5) and (9) generating smaller MADs and MDSs than the three-week moving average, the question was which alternative is preferred? Again, a simple t-test at the 0.05 level of confidence was applied. At this level, the test indicated that alternatives (5) and (9) are not significantly different. With this fact in mind, alternative (5) would be preferred to (9) because of computational ease.²

While it was possible to use a simple t-test to arrive at a preferred method of forecasting, the results of the various methods have indicated the true randomness of the cargo flow into the Container Stuffing Station. No one

²Table XII, Appendix A, shows a sample of the t-test calculations.

particular method dominates the others in its ability to accurately forecast the weekly volume inputs for all of the major PODs. The satisfaction of arriving at a preferred method must come from the fact that this method does result in deviations that are smaller than those generated by a three-week moving average and is computationally easier and less sensitive to the data than another method that is comparable in its forecasting accuracy.

Additionally, the minimum MADs achieved using alternative (9) occurred at γ -levels ranging from -1.00 to +0.49. Also, the data for most PODs possessed several maxima and minima of MAD as γ -levels were varied. This revealed the highly sensitive nature of the results of forecasts to the input data when alternative (9) was used. Should the characteristics of these data change in future observations, errors resulting from the continued use of previously optimal γ -levels could become substantial. This was contrasted to the more narrow range of α -levels (from 0.02 to +0.77) for alternative (5) and the achievement of a single minimum MAD for most cases.

Computer Output Three-One and Computer Output Five-One are representative of these relationships.

7. Forecast Variance Estimation

To this point, this thesis has been concerned with the choice of an optimal method of forecasting the volume inputs to the CSS, using mean absolute deviation and mean deviation squared as the criterion of goodness. The application of any method chosen requires that the statistical

variance of the forecast be known or estimated such that confidence in the forecast may be assessed. The knowledge of the variance can assist the booking of vans by providing a means of assessing the impacts and costs of conservative versus aggressive booking policies and the probable effects on average age of cargo, cancellations, cargo volume on the floor, cube utilization and other policies. Just as the expected volume was forecast by some method, so must the expected variance be forecasted or estimated. Two possible procedures for arriving at variances for the forecasts are suggested.

The first possible method of estimating the variance and standard deviation of volume inputs for a POD could be to project forward historical information for one period to the next. If this method were chosen, the length of the period would dictate how much averaging out of fluctuations would be accomplished. Conversely, should the fluctuations be tied to some major policy decisions occurring during a period, variance estimates could be seriously in error if the period chosen was too long. It is suggested that perhaps a period of six months to one year, providing 26 to 52 weekly deviation observations. Thus, the weekly volume input variance for a POD calculated for one period could be applied to all weekly forecasts for that POD in the ensuing period.

Utilization of a smoothed square deviation computed simultaneously with each volume forecast is another possible method of estimating the variance. As the variance of each

forecast is related to the square of the deviation between the observed and forecasted volume for the period, this value could be smoothed from one forecasting period to the next using the simple exponentially weighted average technique. The estimated standard deviation for the next forecast could be calculated as the square root of the smoothed squared deviation. The value of the smoothing constant (alpha) for this calculation could be selected depending on the weight to be placed on the most recent data (usually between 0.1 and 0.3 according to Brown [Ref. 3]). Intuitively, the selection of a larger alpha could be tied to more aggressive booking policies by trying to detect recent trends while smaller values would provide more conservative long-run averages. In any case, this technique provides continual updating of variance estimates.

Neither of these methods was tested pursuant to this thesis due to the limitation of having only one year's data and the lack of any apparent measure of goodness that would indicate the relative optimality of one method over the other.

Whether or not either of these methods is used, some estimates of the variance associated with a forecast prediction is imperative to establish consistency between the booking policy and other policies concerned with the movement through and storage within the Container Stuffing Station.

D. CRITIQUE OF PROCEDURES AND DATA ANALYSIS

The analysis leading up to and including the forecasting techniques have been presented in detail in the preceding sections of this chapter. This section will evaluate the procedures used to make the analysis.

1. Distribution Audit

The distribution audit was a necessary first step in the data analysis. Although there was a multitude of information available concerning the cargo arriving at MOTBA, only the number of shipments, their volume and their weight was of concern to this work. The audit took the raw data and placed it in a meaningful format.

The distribution audit helped to establish the fact that the Vietnam conflict generated a tremendous cargo flow. Therefore, it was decided not to use the six months of data from FY '73. This left 52 weeks of data for FY '74, providing a reasonable number of observations. Another alternative would have been to exclude the data for the first two months of FY '74, because this data had large volume fluctuations on a scale similar to FY '73 data. The exclusion of this data may have resulted in the generation of lower deviations for any or all of the forecasting techniques that were applied.

Since there was a requirement to book container space aboard vessels three weeks in advance, the data was grouped in weekly intervals resulting in 52 observations for the period. Although biweekly data could have been used,

it was more convenient to use weekly intervals for the data analysis. Intervals greater than two weeks would have resulted in too few observations.

The distribution audit also identified the number of shipments classified as release unit because of weight. These shipments were considered part of the random volume flow based on the fact that they comprised a very small percentage of the total number of shipments.

In short, the distribution audit provided a starting point for the procedures that followed. It simplified the data by placing it in meaningful perspective.

2. Serial Correlation Test

The data was analyzed to reveal the presence of serial correlation. The Durbin-Watson d-Statistic Test is commonly used for the purpose. The calculations for the test were easily accomplished by computer programming. The data was tested using weekly and biweekly intervals. Tri-weekly intervals were not used since they would have resulted in only 17 observations. The results of the test justified the application of the forecasting methods previously discussed.

3. Forecasting Methods

a. Moving Average Method

The moving average was the most obvious method to initially apply to the data. It provided a simple means of forecasting future volume inputs. Less weight was given to the weekly input as the time interval for the moving

average was increased. Time intervals from one to ten weeks were evaluated. To carry the evaluation beyond ten weeks would have been superfluous since time intervals beyond ten weeks result in minimal changes in the forecasts for each new input of data. As the moving average intervals become large, the process approaches the use of the mean of the volume inputs over a certain time period (for example, a quarter) as a forecast for the next similar period. The calculations indicated that increased smoothing of the data was accomplished by increasing the time interval of the moving average beyond three weeks.

b. Exponentially Weighted Average Methods

While previous discussions may have indicated that there were four forecasting techniques applied to the data, in reality there were only two -- the moving average and the EWA plus two variations.

The EWA method, unlike the moving average, considers all past data to some extent. Through the application of the smoothing constant, the emphasis placed on the most recent data can be varied.

One variation of the EWA was to adjust for trend effects in the data. The apparent trend was then smoothed and combined with a smoothed forecasted average to make a forecast for the following week.

The second variation was the application of an adaptive response rate to the EWA. This particular ARR used a smoothed error term to calculate a tracking signal. Other

methods for calculating a tracking signal may be available; but they were not investigated.

When the EWA methods were applied to the data, deviations were calculated beginning with the third week. For the moving average method, deviations were not computed until the week following the length of the time interval. In order to evaluate the methods it may have been more appropriate to begin calculating the deviations for the EWA methods in the eighth, ninth or tenth week.

4. Data

The time period covered by the data was another limitation in the application of the forecasting techniques. In general, time-series analysis covers a three to four year period with data being grouped by months or even quarters. Conditions for this analysis were far from being optimal.

The fact that there was only a year's data also precluded investigation of seasonal or cyclic effects. Again, a three to four year period is usually required before smoothing techniques can be applied to the data.

In summary, the breakdown of the yearly data into weekly intervals constituted the most logical approach to the problem. While a year of data did not represent a long period of time, it did represent the best that was available at the time.

V. CONCLUSION

This thesis concerned itself with the forecast of the volume of cargo flowing into the Container Stuffing Station at MOTBA destined for a particular port of debarkation. The data used in this work was taken from actual operations at the CSS during FY '74. Although every system is capable of generating errors, it was assumed that any errors were minimal and that the data was correct.

Prior to utilizing any forecasting techniques, the data was analyzed in three phases: a distribution audit; the grouping of data into weekly intervals by POD; and a test for serial correlation.

This thesis made use of the distribution audit of McCarthy and Carter. The purpose of the audit was to simplify the large volume of raw data generated by the operations at MOTBA. The magnitude of the operations at the CSS is illustrated by the following information. During FY '74 there were a total of 124,592 shipments weighing over 176 million pounds and with a total volume of 10,070,724 cubic feet. These shipments were destined for 3,356 consignees in 157 overseas ports. Sixteen major ports accounted for 93% of the shipments, 93% of the volume and 91% of the weight. These 16 PODs then became the focal point for further analysis.

The grouping of the data into weekly intervals by POD indicated the large volume fluctuations that occurred for

most of the 16 PODs under consideration. Plots of the weekly volume inputs revealed the lack of any set pattern of cargo flow from POD to POD. Before making any decisions as to which forecasting techniques to apply, it was necessary to determine whether the data was random in nature or correlated from one observation to the next; that is, serially correlated. The Durbin-Watson d-Statistic Test satisfied this requirement. A computer program was written to compute the d-statistic and to compare it with critical values. Using weekly volume inputs the test indicated that 9 of 16 PODs had serial correlation in the data. Another test was performed by grouping the data into biweekly intervals. Similar results were obtained. The preceding results were then tested to determine if there was serial correlation present in the data. The test was affirmative.

The results of the serial correlation test supported the use of forecasting methods other than ordinary least-squares trending. The simplest and most logical forecasting methods to apply to the data were the moving average method and the exponentially weighted average method. Two variations were applied to the exponentially weighted average resulting in a total of four methods.

In order to evaluate the forecasting methods on an equal basis, the mean absolute deviation and the mean deviation squared were used, the deviation being the difference between the forecast and the actual input. Four computer programs were written to calculate the MADs and MDSs for the various forecasting methods.

Moving averages from one to ten weeks were applied to the data. The MAD and MDS for each time interval were calculated by computer program. The EWA method used a smoothing constant to generate the forecast. Various levels of the constant were applied to the data. A variation of the EWA calculated the apparent trend of the data. This apparent trend and the forecasted average were then smoothed and added to get the forecast for the following week. Another variation to the EWA method was the application of an adaptive response rate. The ARR uses a tracking signal which is computed by taking the sum of the differences between the forecast and the actual input volume for each week and dividing this total into the sum of the absolute values of those differences. As each error becomes available it is smoothed along with the old error. The smoothing constant to be used in forecasting is then set equal to the absolute value of the tracking signal and then the EWA is applied as before.

The deviation statistics resulting from the application of the above forecasting methods to the actual data with a one-week time horizon were tested using the Student t-distribution. This test revealed that the EWA and ARR methods using the individual POD's optimal smoothing constants were statistically the same and better than all other methods. The EWA technique was then chosen as preferred based on its computational ease relative to ARR.

The selection of the EWA method offered some advantages over the three-week moving average being used at the CFD.

First, EWA was computationally no more difficult. It derived its advantage by responding to changes in volume more uniformly than the abrupt alterations that the three-week moving average caused in the forecasts. Also, the accumulation of a historical data base in the smoothed forecast average increased the accuracy of the EWA method as the time horizon increased. Decreases of 4.9%, 8.0% and 10.0% in mean absolute deviations for the one-, two-, and three-week time horizons using the EWA method evidenced the increase in accuracy. For this application and data, there can be little doubt that the use of the EWA provided improvement in the forecasting techniques.

The other forecasting methods retained their relative merits. Greater accuracy was achieved using moving averages by increasing the lengths of the averaging interval at the expense of increasing the computational difficulty. The absence of any apparent trend in the data resulted in lack of any additional benefits from trend adjustments. While the adaptive response rate technique showed no real advantage over the EWA method for this data, its ability to respond rapidly to major policy changes makes it a viable alternative at the expense of increased computational difficulty. As more data becomes available, all of these methods deserve additional consideration and thoughtful attention as the results of this work are based on only a year's data.

Although significant increases in forecasting have been achieved, there remains in the data large amounts of randomness

causing significant errors. Its random nature, without trends or significant shifts, have led to the evolution of the exponentially weighted average method as the preferred choice. As more data is accumulated the other methods may be reexamined. The optimal smoothing constants should be updated periodically to account for changes in the data and promote long run efficiency of the method. However, the most important safeguard against costly mistakes due to random effects in the input volume is careful managerial scrutiny of each forecast generated and used to make a booking. Judgment on the reasonableness of a prediction makes the manager the final and ultimate smoothing factor in the utilization of the forecast.

APPENDIX A

<u>WEEK</u>	<u>SHIPMENTS</u>	<u>VOLUME</u>	<u>WEIGHT</u>
27	3,208	220,991	3,925,310
28	5,091	413,602	7,164,543
29	4,598	336,189	6,062,987
30	4,884	368,350	6,038,153
31	5,707	344,109	6,312,502
32	4,727	372,533	6,281,837
33	4,726	358,880	6,640,755
34	4,214	303,929	5,393,130
35	5,681	378,598	7,275,388
36	5,031	324,176	6,206,201
37	5,045	348,497	6,760,475
38	4,638	301,952	5,808,959
39	4,384	303,536	5,719,112
40	4,047	300,089	5,138,948
41	4,646	335,702	6,322,970
42	4,753	343,370	6,425,117
43	4,317	314,323	5,969,897
44	3,935	281,744	5,190,323
45	3,906	253,313	4,840,206
46	3,318	248,060	4,473,395
47	3,660	288,476	5,085,827
48	2,957	231,423	4,205,199
49	3,498	320,646	5,902,697
50	3,338	285,413	1,150,959
51	3,675	387,533	5,980,555
52	3,579	433,497	6,248,080

Note: (1) Volume is in cubic feet
(2) Weight is in pounds

Table I. Gross Weekly Inputs. Weeks 27 through 52, FY '73.

<u>WEEK</u>	<u>SHIPMENTS</u>	<u>VOLUME</u>	<u>WEIGHT</u>
1	2,444	261,448	3,921,219
2	2,797	287,444	4,527,403
3	3,141	278,991	4,997,954
4	2,758	232,296	3,571,542
5	3,414	284,814	5,151,369
6	4,044	308,446	5,844,244
7	965	88,024	1,484,204
8	2,905	208,179	3,908,164
9	2,641	196,694	3,625,615
10	1,994	164,170	3,017,826
11	2,425	206,833	3,837,876
12	2,787	215,422	4,308,528
13	2,485	199,702	4,533,820
14	2,541	192,863	3,600,097
15	1,784	135,561	2,378,525
16	2,653	194,927	3,742,275
17	1,983	150,028	2,857,312
18	1,387	111,154	2,199,669
19	2,340	208,560	3,761,167
20	2,411	184,520	3,200,648
21	1,361	105,629	1,965,960
22	2,414	149,722	3,663,732
23	2,927	203,497	3,864,209
24	2,754	199,888	3,695,823
25	2,757	189,969	3,657,957
26	1,523	130,513	2,592,805

Note: (1) Volume is in cubic feet
(2) Weight is in pounds

Table II. Gross Weekly Inputs. Weeks 1 through 26, FY '74.

<u>WEEK</u>	<u>SHIPMENTS</u>	<u>VOLUME</u>	<u>WEIGHT</u>
27	1,530	135,843	2,186,285
28	2,956	232,446	3,841,574
29	3,058	260,123	4,468,724
30	2,338	179,400	3,078,738
31	2,580	241,953	3,793,319
32	2,814	242,661	4,034,761
33	2,667	211,740	3,470,228
34	1,585	139,665	2,459,631
35	3,007	267,702	4,907,835
36	2,083	164,209	2,725,845
37	1,994	143,360	2,385,097
38	2,198	145,621	2,851,101
39	2,557	172,236	3,151,837
40	2,247	170,630	2,921,166
41	2,060	201,845	3,388,849
42	2,145	195,070	3,211,454
43	2,041	191,623	3,135,205
44	2,704	198,084	3,052,520
45	2,381	204,956	3,269,329
46	2,189	193,582	3,264,435
47	2,739	177,121	3,355,770
48	1,395	96,791	1,628,575
49	2,227	185,867	2,771,581
50	2,522	194,153	2,716,456
51	2,812	229,928	3,602,602
52	2,228	188,520	2,631,603

Note: (1) Volume is in cubic feet
(2) Weight is in pounds

Table II. Gross Weekly Inputs. Weeks 27 through 52, FY '74.
(Continued)

Period analyzed - FY '74	365 days
Shipments	124,592 shipments
Volume of cargo	10,070,724 cubic feet
Weight of cargo	176,213,333 pounds
Number of PODs	157
Number of consignees	3,356

Table III. Data Summary for the Distribution Audit.

SHIPMENTS

Total shipments of 16 PODs	115,732 shipments
Total shipments of all PODs	124,592 shipments
Percentage of total shipments	92.89%

VOLUME

Total volume of 16 PODs	9,370,693 cubic feet
Total volume of all PODs	10,070,724 cubic feet
Average volume/shipments (16 PODs)	87 cubic feet
Percentage of total volume (16 PODs)	93.05%

WEIGHT

Total weight of 16 PODs	160,575,726 pounds
Total weight of all PODs	176,213,333 pounds
Average weight/shipments (16 PODs)	1,387.47 pounds
Percentage of total weights (16 PODs)	91%

Table IV. Tabular Data for 16 Major PODs, FY '74.

<u>POD</u>	<u>SHIPMENTS</u>	<u>VOLUME</u>	<u>WEIGHT</u>
RA3	20,125	1,474,747	28,284,704
RGU	6,041	491,465	11,486,615
RG1	1,850	170,766	3,774,348
RJ1	2,848	170,635	3,323,333
RJ3	2,210	106,150	1,802,072
SA3	16,837	1,377,838	19,920,384
TA1	2,502	120,073	2,132,222
TA2	6,793	502,989	7,269,693
UB1	12,339	1,081,519	19,311,360
UC2	6,593	976,869	19,325,856
UD6	8,691	451,466	9,062,837
UL7	3,183	233,232	4,445,639
UM1	6,619	434,615	7,081,348
UM4	3,769	276,100	3,740,452
XE2	14,008	1,315,539	16,679,435
XJ1	1,324	186,690	2,935,428

Note: (1) Volume is in cubic feet

(2) Weight is in pounds

Table V. POD Data - 16 PODs, FY '74.

<u>POD</u>	<u>NUMBER OF RU SHIPMENTS</u>	<u>PERCENTAGE OF RU SHIPMENTS</u>
RA3	384	1.90
RGU	156	2.58
RG1	37	2.00
RJ1	41	1.43
RJ3	15	0.68
SA3	183	1.00
TA1	15	0.59
TA2	86	1.26
UB1	242	1.96
UC2	327	4.90
UD6	80	0.92
UL7	43	1.35
UM1	80	0.92
UM4	20	0.53
XE2	136	0.97
XJ1	<u>55</u>	4.15
TOTAL	1,900	

The percentage of RU shipments to the total number of shipments for the 16 major PODs is 1.64%.

Table VI. Release Unit Shipments.

POD	WEEK INT	WEEK START	NO. OBS	d-STATISTIC MEANING	POD	WEEK INT	WEEK START	NO. OBS	d-STATISTIC MEANING
RA3	1	1	52	INCN	UB1	1	1	52	NONE
	2	1	26	INCN		2	1	26	NONE
	2	2	25	POSI		2	2	25	NONE
RGU	1	1	52	POSI	UC2	1	1	52	NONE
	2	1	26	INCN		2	1	26	INCN
	2	2	25	INCN		2	2	25	INCN
RG1	1	1	52	POSI	UD6	1	1	52	INCN
	2	1	26	POSI		2	1	26	NONE
	2	2	25	POSI		2	2	25	NONE
RJ1	1	1	52	POSI	UL7	1	1	52	POSI
	2	1	26	NONE		2	1	26	POSI
	2	2	25	NONE		2	2	25	POSI
RJ3	1	1	52	NONE	UM1	1	1	52	POSI
	2	1	26	NONE		2	1	26	NONE
	2	2	25	NONE		2	2	25	POSI
SA3	1	1	52	POSI	UM4	1	1	52	POSI
	2	1	26	INCN		2	1	26	NONE
	2	2	25	POSI		2	2	25	POSI
TA1	1	1	52	INCN	XE2	1	1	52	POSI
	2	1	26	POSI		2	1	26	POSI
	2	2	25	INCN		2	2	25	POSI
TA2	1	1	52	INCN	XJ1	1	1	52	POSI
	2	1	26	INCN		2	1	26	POSI
	2	2	25	INCN		2	2	25	INCN

Note: (1) POSI = the test indicated POSITIVE serial correlation
(2) INCN = the test was INCONCLUSIVE
(3) NONE = the test indicated no serial correlation

Table VII. Serial Correlation Test Results.

Table VIII. MADs for 16 PODs.
One-week time horizon

<u>POD</u>	<u>TWMA</u>	<u>t</u>	<u>OMA</u>	<u>α</u>	<u>EWA</u>	<u>α</u>	<u>EWA-TA</u>	<u>γ</u>	<u>EWA-ARR</u>
RA3	6797*	3	6797*	.36	7021	.11	7186	-.78	7074
RGU	3910	6	3733	.27	3599*	.13	3717	.40	3633
RG1	1754	10	1467*	.60	1709	.34	1787	.34	1611
RJ1	1793	9	1462*	.35	1734	.14	1770	.01	1604
RJ3	1130	8	1064	.21	1083	.11	1066	-.01	1030*
SA3	7862	3	7862	.04	7458*	.02	7461	-.05	7974
TA1	996	5	811	.22	935	.10	961	.13	395
TA2	3654	10	3498	.40	3505	.18	3469*	-.02	3484
UB1	5321	7	5040*	.24	5112	.10	5174	-.85	5216
UC2	5236	7	4583*	.10	4940	.04	4839	-.17	4794
UD6	4205	7	3718	.28	3845	.11	3893	-.07	3372*
UL7	1383	5	1296	.20	1290	.12	1358	.38	1287*
UM1	3637	10	3341	.54	3300	.10	3311	-.10	3161*
UM4	2521	8	2366	.48	2380	.21	2490	.11	2355*
XE2	7770	10	7391	.47	7615	.26	7787	.07	7130*
XJ1	2743	2	2564	.43	2434*	.21	2657	-1.00	2475

- Note:
- (1) MAD = Mean Absolute Deviation
 - (2) POD = Port of Debarkation
 - (3) TWMA = Three Week Moving Average
 - (4) OMA = Optimal Moving Average
 - (5) t = time interval (in weeks) for OMA
 - (6) EWA = Exponentially Weighted Average
 - (7) α = smoothing constant for EWA and EWA-TA
 - (8) EWA-TA = Exponentially Weighted Average with Trend Adjustment
 - (9) EWA-ARR = Exponentially Weighted Average with Adaptive Response Rate
 - (10) γ = smoothing constant for EWA-ARR
 - (11) MADs are expressed in cubic feet

*Indicates smallest MAD for POD

Table VIII. MADs for 16 PODs (Continued).

Two-week time horizon

<u>POD</u>	<u>TWMA</u>	<u>t</u>	<u>OMA</u>	<u>α</u>	<u>EWA</u>	<u>α</u>	<u>EWA-TA</u>	<u>γ</u>	<u>EWA-ARR</u>	
RA3	6204	3	6204	.32	5955*	.17	6293	-	.89	6095
RGU	3621	3	3621	.09	32.84*	.22	3489		.45	3339
RG1	1601	10	1362	.77	1572	.37	1690		.23	1311*
RJ1	1350	8	1194*	.37	1420	.17	1449		.01	1292
RJ3	850	3	850	.28	804	.11	801		.01	750*
SA3	6639	3	6639	.02	6250	.01	6247*	-	.05	6927
TA1	798	6	595*	.22	701	.12	729		.11	694
TA2	3194	10	3056	.39	3072	.17	3125	-	.03	2991*
UB1	4655	7	4250	.15	4246	.06	4179*	-	.01	4417
UC2	4001	7	3150*	.15	3399	.06	3278	-	.10	3423
UD6	3688	7	3135	.27	3235	.10	3268	-	.08	2938*
UL7	1053	4	1005*	.28	1013	.17	1082	-	.44	1033
UM1	3146	10	2641	.19	2816	.09	2893		.01	2615
UM4	2343	9	2153	-.02	1878	-.01	1847*		.10	2177
XE2	6984	3	6984	.65	6697	.31	6941	-	.01	6269*
XJ1	2771	10	2327*	.23	2435	.10	2592	-	.75	2452

*Indicates smallest MAD for POD

Table VIII. MADs for 16 PODs (Continued).

Three-week time horizon

<u>POD</u>	<u>TWMA</u>	<u>t</u>	<u>OMA</u>	<u>α</u>	<u>EWA</u>	<u>EWA-TA</u>		<u>EWA-ARR</u>	
						<u>α</u>		<u>\bar{Y}</u>	
RA3	6620	8	6197	.26	5910	.10	6069	- .74	6351
RGU	3477	5	3410	.13	3120*	.04	3382	- .47	3214
RG1	1652	10	1363	.75	1498	.37	1529	.25	1245*
RJ1	1188	7	1036*	.43	1253	.25	1296	.01	1086
RJ3	863	10	824	.31	789	.09	784	.01	713*
SA3	6451	7	6388	.34	5848	.01	5238*	-1.00	6234
TA1	721	5	545*	.25	626	.13	653	.14	561
TA2	3149	10	2660*	.31	3030	.17	2990	- .03	2789
UB1	3627	7	3252	.18	3225	.07	3187*	- .01	3471
UC2	3390	10	2548*	.19	2830	.06	2781	-1.00	2652
UD6	3326	10	2981	.29	2988	.11	3147	- .07	2410*
UL7	972	5	937*	.29	946	.16	995	- .46	978
UM1	3215	10	2355	.19	2675	.09	2681	- .12	2331*
UM4	2327	9	1970	-.01	1709*	.01	2051	- .01	2127
XE2	6831	10	6717	.55	6778	.30	6960	- .01	5971*
XJ1	2787	10	2049*	.17	2308	.09	2422	.75	2386

*Indicates smallest MAD for POD

Table IX. MDSs for 16 PODs
One-week time horizon

POD	TWMA	t	OMA	α	EWA	α	EWA-TA	γ	EWA-ARR
RA3	92,564	7	90,250*	.30	93,854	.06	98,367 -	.82	98,528
RGU	27,737	4	27,546	.32	24,977*	.14	26,690 -	.59	25,060
RG1	10,349	10	5,769*	.60	10,736	.30	10,117	.25	8,805
RJ1	5,741	8	3,691*	.33	5,337	.16	5,511	.02	5,474
RJ3	2,825	7	2,591	.12	2,455*	.05	2,481 -	.55	2,455
SA3	96,136*	3	96,136*	.38	98,728	.04	104,177 -	1.00	104,207
TA1	1,659	6	1,184*	.21	1,545	.12	1,611	.11	1,614
TA2	22,695	10	19,113*	.28	20,456	.12	21,253 -	.03	20,549
UB1	51,088	7	41,265*	.14	42,697	.06	43,547 -	.78	44,880
UC2	41,418	9	30,695*	.14	35,775	.05	34,811 -	1.00	35,382
UD6	34,556	7	30,086	.25	29,872	.13	31,267 -	.07	27,730*
UL7	3,453	5	3,195	.28	3,183	.16	3,267 -	.44	3,176*
UM1	25,750	10	23,983	.24	22,108	.11	23,010 -	.14	21,463*
UM4	11,870	8	9,145*	.28	9,936	.07	10,610 -	.86	10,500
XE2	102,515	10	84,346*	.52	103,848	.25	106,797	.05	90,932
XJ1	15,387	2	13,530	.48	12,845	.16	14,115 -	.13	12,490*

- Note:
- (1) MDS = Mean Deviation Squared
 - (2) POD = Port of Debarkation
 - (3) TWMA = Three Week Moving Average
 - (4) OMA = Optimal Moving Average
 - (5) t = time interval (in weeks) for OMA
 - (6) EWA = Exponentially Weighted Average
 - (7) α = smoothing constant for EWA and EWA-TA
 - (8) EWA-TA = Exponentially Weighted Average with Trend Adjustment
 - (9) EWA-ARR = Exponentially Weighted Average with Adaptive Response Rate
 - (10) γ = smoothing constant for EWA-ARR
 - (11) MDSs are in 1,000's and expressed in (cubic feet)²

*Indicates smallest MDS for POD

Table IX. MDSs for 16 PODs
(continued)

Two-week time horizon

<u>POD</u>	<u>TWMA</u>	<u>t</u>	<u>OMA</u>	<u>α</u>	<u>EWA</u>	<u>α</u>	<u>EWA-TA</u>	<u>γ</u>	<u>EWA-ARR</u>
RA3	70,264	7	69,626	.18	62,116*	.05	64,218	-.82	69,925
RGU	21,534	5	20,533	.27	18,672*	.12	20,411	-.53	18,829
RG1	9,064	10	5,293*	.69	8,385	.36	7,121	.22	5,588
RJ1	3,732	8	2,413*	.32	4,019	.16	4,165	.01	3,965
RJ3	1,659	10	1,388	.13	1,327*	.06	1,360	-.55	1,334
SA3	76,062	3	76,062	.07	73,856*	.03	73,992	-1.00	80,384
TA1	1,060	6	749*	.22	953	.13	1,018	.11	948
TA2	16,801	10	12,717*	.26	14,376	.11	15,107	-.03	13,101
UB1	30,872	7	24,900*	.14	25,001	.06	25,749	-.01	27,513
UC2	25,069	10	14,927*	.15	18,843	.06	17,843	-1.00	17,496
UD6	24,416	10	20,683	.23	21,071	.12	22,598	-.07	17,668*
UL7	2,084	4	1,880*	.30	1,952	.17	2,021	-.47	1,977
UM1	19,208	10	15,958	.20	16,063	.10	16,948	-.01	14,948*
UM4	10,062	9	6,781*	.15	7,909	.01	8,057	-.01	8,216
XE2	81,399	2	80,557	.54	79,063	.26	81,152	-.01	60,822*
XJ1	13,673	10	10,908*	.31	11,087	.13	12,110	-.14	11,067

*Indicates smallest MDS for POD

Table IX. MDSs for 16 PODs
(continued)

Three-week time horizon

<u>POD</u>	<u>TWMA</u>	<u>t</u>	<u>OMA</u>	<u>α</u>	<u>EWA</u>	<u>α</u>	<u>EWA-TA</u>	<u>γ</u>	<u>EWA-ARR</u>
RA3	69,762	8	64,618	.10	54,579*	.04	55,583	-.78	67,596
RGU	19,006	4	18,391	.26	16,418*	.11	18,245	-.51	16,570
RG1	10,187	10	5,461*	.75	8,571	.38	6,724	.24	5,822
RJ1	2,737	10	1,871*	.33	3,234	.18	3,354	-.01	2,968
RJ3	1,347	9	1,035	.14	967*	.06	1,002	-.55	969
SA3	74,786	3	74,786	.05	61,446	.02	61,394*	-1.00	73,494
TA1	806	10	663	.26	712	.14	779	.11	635*
TA2	15,444	10	9,783*	.24	12,773	.10	13,408	-.03	10,545
UB1	18,965	4	16,064	.17	15,866*	.07	16,757	-.01	17,603
UC2	19,213	10	10,170*	.16	13,467	.06	12,539	-1.00	11,723
UD6	20,080	10	15,516	.24	16,499	.13	18,160	-.07	12,549*
UL7	1,633	4	1,551*	.33	1,570	.18	1,638	.49	1,621
UM1	17,862	10	12,662	.19	13,577	.10	14,584	-.12	11,984*
UM4	8,787	8	5,197*	.01	6,067	.01	6,217	-.69	7,084
XE2	81,188	10	75,150	.53	79,907	.26	80,197	-.01	54,919*
XJ1	13,778	10	8,106*	.23	10,803	.12	11,790	-.94	10,820

*Indicates smallest MDS for POD

WEEKLY TIME HORIZON	TWMA	t	OMA ₁	OMA ₂	α	EWA ₁	EWA ₂	α	EWA-TA ₁	EWA-TA ₂	γ	ARR ₁	ARR ₂
one	60,712	7	59,209	56,993	.36	59,387	57,756	.16	61,291	58,926	-.05	59,676	57,135
two	52,998	10	51,287	49,116	.35	51,556	48,777	.11	55,335	49,903	-.05	51,609	48,723
three	50,596	10	46,773	45,232	.33	48,382	45,533	.16	51,031	46,165	-.04	48,080	44,519

Note:

- (1) MAD = Mean Absolute Deviation
- (2) OMA₁ = Optimal Moving Average (a specific optimal interval is applied to all POD data)
- (3) OMA₂ = Optimal Moving Average (optimal intervals are applied to each POD)
- (4) t = weekly interval for OMA₁
- (5) EWA₁ = Exponentially Weighted Average (an optimal α-level is applied to all the POD data)
- (6) EWA₂ = Exponentially Weighted Average (optimal α-levels are applied to each POD's data)

- (7) EWA-TA₁ = EWA with Trend Adjustment (an optimal α-level is applied to all the POD data)
- (8) EWA-TA₂ = EWA with Trend Adjustment (optimal α-levels are applied to each POD's data)
- (9) α = smoothing constant for EWA and EWA-TA
- (10) ARR₁ = Adaptive Response Rate (an optimal γ-level is applied to all POD data)
- (11) ARR₂ = Adaptive Response Rate (optimal γ-levels are applied to each POD's data)
- (12) γ = smoothing constant for ARR
- (13) MAD is in cubic feet

Table X. Aggregate MADs for 16 PODs.

WEEKLY TIME HORIZON	TWMA	t	OMA	α	EWA	α	EWA-TA	γ	ARR
one	545,749	7	523,120	.37	535,979	.17	566,904	-.14	543,745
two	406,966	10	391,469	.36	388,940	.17	421,432	-.05	393,060
three	375,569	10	341,400	.36	350,451	.17	384,810	-.05	346,852

Note:

- (1) MDS = Mean Deviation Squared
- (2) OMA = Optimal Moving Average (a specific optimal interval is applied to all POD data)
- (3) EWA = Exponentially Weighted Average (a specific optimal α -level is applied to all POD data)
- (4) EWA-TA = Exponentially Weighted Average with Trend Adjustment (a specific α -level is applied to all POD data)
- (5) ARR = Adaptive Response Rate (a specific optimal γ -level is applied to all data)
- (6) t = optimal time interval for OMA
- (7) α = smoothing constant for EWA and EWA-TA
- (8) γ = smoothing constant for ARR
- (9) MDSs are expressed in (cubic feet)²

Table XI. Aggregate MDSs for 16 PODs.

In this work the Student t-distribution was used to resolve whether the mean of the MAD differences between two forecasting methods was equal to zero.

The hypotheses were:

$$H_0: \mu = 0, \quad H_1: \mu \neq 0.$$

The t-test utilizes the following

$$t = \frac{(\bar{X} - \mu) \sqrt{n}}{s}$$

where \bar{X} is the sample mean, $\mu=0$, n =number of observations and s =the sample standard deviation.

Calculated values of t are compared with critical values of t . If

$$t \text{ (calculated)} < t \text{ (critical)}$$

H_0 is accepted

If $t \text{ (calculated)} > t \text{ (critical)}$

H_0 is not accepted.

If H_0 is not accepted, the two methods are different and the method that generates the lowest mean absolute deviation is chosen as the preferred.

The test only utilized deviations generated by a one-week time horizon.

Table XII. t-Test Procedure.

COMPUTER OUTPUT ONE

TABLE OF STATISTICAL DATA FOR SFLCTED PODS USING WEEKLY TOTAL VOLUME (CU. FT.) DATA

POD	INTERVAL	START	INTERCEPT	SLOPE	STD. ERR.	R-SQUARE	D-STAT	OBS.	MEANING
	1	1	0.	0.41467E 00	175.1	0.00131	1.60872	52	NONE
	2	1	125.	0.17819E 01	247.5	0.00315	1.34558	26	INCN
	2	2	18.	0.82701E 01	239.2	0.06791	1.90606	25	NONE
AC2	1	1	2.	0.99676E -01	28.4	0.00288	2.07288	52	NONE
	2	1	5.	0.35365E 00	40.2	0.00469	2.14859	26	NONE
	2	2	7.	0.31176E 00	40.3	0.00363	2.16524	25	NONE
AF4	1	1	56.	-0.11562E 01	153.9	0.01717	1.99740	52	NONE
	2	1	115.	-0.49520E 01	167.7	0.03414	1.11634	26	POSI
	2	2	40.	-0.48411E -01	183.2	0.00273	0.98535	25	POSI
BA1	1	1	973.	-0.14174E 01	1589.2	0.00019	1.79631	52	NONE
	2	1	1936.	-0.48123E 01	2432.2	0.00024	1.75145	26	NONE
	2	2	1901.	-0.66251E 01	2300.8	0.05028	1.92076	25	NONE
BA3	1	1	3.	-0.57628E -01	12.6	0.00490	2.04927	52	NONE
	2	1	6.	-0.21539E 00	17.9	0.00871	2.03843	26	NONE
	2	2	220.	-0.12810E 02	277.3	0.11508	0.11955	25	POSI
BA4	1	1	184.	-0.11361E 01	383.1	0.00195	1.69409	52	NONE
	2	1	373.	-0.47521E 01	524.6	0.00498	1.68739	26	NONE
	2	2	441.	-0.13197E 02	621.2	0.02677	2.14396	25	NONE
CA2	1	1	-9.	0.54517E 00	40.8	0.04024	2.12489	52	NONE
	2	1	-17.	0.21323E 01	57.1	0.07649	2.25849	26	NONE
	2	2	44.	-0.13184E 01	101.7	0.01014	1.74070	25	NONE
CA3	1	1	1.	-0.21515E -01	3.3	0.00960	2.05302	52	NONE
	2	1	2.	-0.90256E -01	4.8	0.02151	2.12611	26	NONE
	2	2	8.	-0.44162E 00	9.1	0.12659	1.55852	25	NONE
CB5	1	1	10.	-0.37565E -01	50.6	0.00313	2.07051	52	NONE
	2	1	21.	-0.13051E 00	71.8	0.00335	2.14662	26	NONE
	2	2	19.	-0.20310E -01	71.7	0.00000	2.15491	25	NONE
CL1	1	1	6.	0.23436E -01	38.3	0.00009	2.05264	52	NONE
	2	1	13.	0.35900E -01	54.4	0.00003	2.11631	26	NONE
	2	2	14.	-0.11746E 00	54.4	0.00028	2.11375	25	NONE
CE2	1	1	-0.	0.49091E -02	0.7	0.01151	2.06302	52	NONE
	2	1	-0.	0.18803E -01	1.0	0.02151	2.12611	26	NONE
	2	2	2.	-0.99167E -01	2.9	0.06767	1.03848	25	POSI
CH1	1	1	-1.	0.66166E -01	6.9	0.02091	2.08287	52	NONE
	2	1	-2.	0.55641E 00	9.8	0.04000	2.16737	26	NONE
	2	2	-1.	0.27454E 00	9.8	0.04593	2.20913	25	NONE
CJ1	1	1	0.	0.57629E -02	2.1	0.00176	2.04282	52	NONE
	2	1	0.	0.45841E -01	3.0	0.00444	2.03896	26	NONE
	2	2	0.	0.35371E -01	3.0	0.00345	2.03234	25	NONE
CKA	1	1	275.	-0.42747E 01	394.5	0.02677	1.41554	52	POSI
	2	1	555.	-0.17159E 02	572.3	0.05194	1.60382	26	NONE
	2	2	340.	-0.18553E 01	713.3	0.01205	2.05612	25	NONE
CK1	1	1	71.	-0.11240E 01	129.4	0.01737	1.34041	52	POSI
	2	1	143.	-0.45558E 01	185.9	0.03359	1.11179	26	POSI
	2	2	145.	-0.47130E 01	257.3	0.02347	1.54285	25	NONE
CK2	1	1	135.	-0.30870E 01	278.8	0.02793	2.05219	52	NONE
	2	1	268.	-0.12016E 02	385.5	0.05481	2.18693	26	NONE
	2	2	275.	-0.12970E 02	403.4	0.05927	2.28802	25	NONE
ED1	1	1	0.	-0.73423E -02	0.5	0.04024	2.12487	52	NONE
	2	1	1.	-0.28718E -01	0.8	0.07640	2.25340	26	NONE
	2	2	38.	-0.22517E 01	49.0	0.11411	0.06722	25	POSI
ED3	1	1	0.	-0.31589E -02	0.3	0.02979	2.10197	52	NONE
	2	1	0.	-0.12991E -01	0.4	0.06418	2.22382	26	NONE
	2	2	5.	-0.31976E 00	6.2	0.11932	0.11423	25	POSI
ED4	1	1	25.	-0.36933E 00	32.1	0.03002	1.83209	52	NONE
	2	1	50.	-0.14988E 01	46.6	0.05923	1.64072	26	NONE
	2	2	46.	-0.12378E 01	50.1	0.03582	1.48792	25	NONE

COMPUTER OUTPUT TWO

TABLE OF DEVIATION FOR PODS USING VARIOUS DURATIONS OF MOVING AVERAGES

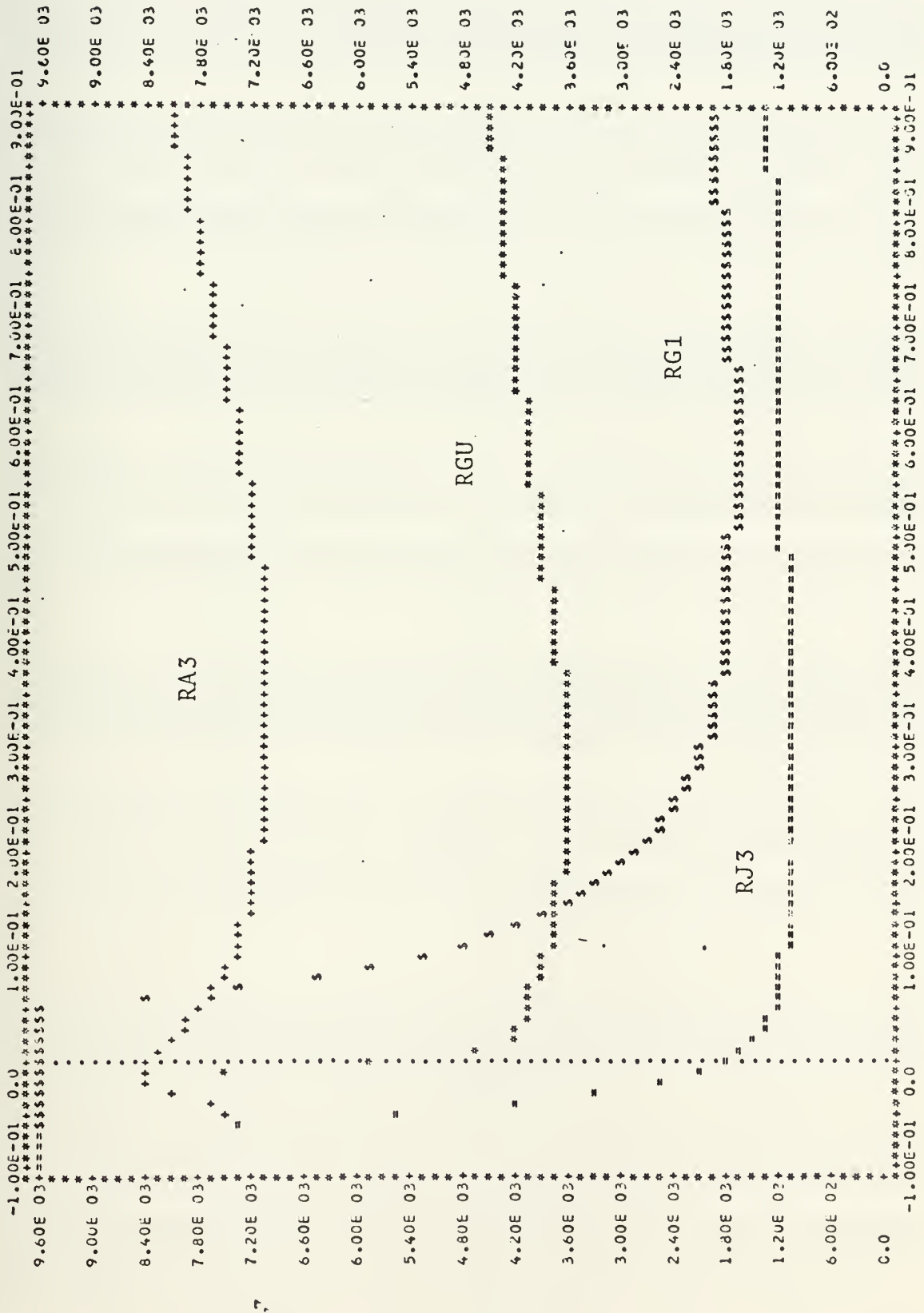
POD	AVG	MAD	MDS	** PGU	AVG	MAD	MDS	** PGD	AVG	MAD	MDS
RA3	1	8599.	130732832.	** RG1	1	2363.	18340640.	** RJ3	1	1359.	4501772.
	2	7651.	195644062.	** RG1	2	1556.	29506656.	** RJ3	2	1130.	3402634.
	3	6797.	32737680.	** RG1	3	1758.	46443019.	** RJ3	3	1130.	2972131.
	4	6673.	94756476.	** RG1	4	1587.	27737824.	** RJ3	4	1097.	2779744.
	5	7142.	101746734.	** RG1	5	1765.	25464288.	** RJ3	5	1134.	2857741.
	6	7314.	99137712.	** RG1	6	1722.	29682900.	** RJ3	6	1077.	27066344.
	7	6941.	90249776.	** RG1	7	1722.	31721943.	** RJ3	7	1070.	2551846.
	8	7070.	92723744.	** RG1	8	1664.	34189099.	** RJ3	8	1084.	2605046.
	9	7177.	93307322.	** RG1	9	1677.	35758559.	** RJ3	9	1069.	2605046.
	10	7452.	94648064.	** RG1	10	1467.	32748048.	** RJ3	10	1075.	2636377.
RJ1	1	1998.	7393937.	** TAI	1	1261.	26334240.	** TAZ	1	4073.	299593152.
	2	1918.	96436396.	** TAI	2	1111.	1200540.	** TAZ	2	3805.	23459252.
	3	1752.	7441244.	** TAI	3	956.	1659151.	** TAZ	3	3654.	22694458.
	4	1572.	4269137.	** TAI	4	892.	1522280.	** TAZ	4	3610.	22414800.
	5	1473.	4087738.	** TAI	5	811.	12244882.	** TAZ	5	3593.	22025322.
	6	1515.	4287733.	** TAI	6	821.	1124082.	** TAZ	6	3796.	22559522.
	7	1473.	3755145.	** TAI	7	829.	1196584.	** TAZ	7	3659.	22559522.
	8	1485.	3651445.	** TAI	8	882.	1196584.	** TAZ	8	3704.	21059262.
	9	1462.	3453551.	** TAI	9	882.	1196584.	** TAZ	9	3549.	21059262.
	10	1515.	3503566.	** TAI	10	878.	13266413.	** TAZ	10	3498.	21911388.
UB1	1	7058.	7269852.	** U06	1	4697.	4090810.	** UL7	1	1785.	5208473.
	2	6166.	66029882.	** U06	2	4423.	38974322.	** UL7	2	1393.	35459744.
	3	5321.	44918008.	** U06	3	4205.	35556628.	** UL7	3	1363.	34510393.
	4	5226.	44607530.	** U06	4	3522.	33325784.	** UL7	4	1308.	327032072.
	5	5304.	45296546.	** U06	5	3840.	33095002.	** UL7	5	1308.	327032072.
	6	5040.	41262216.	** U06	6	3719.	33095002.	** UL7	6	1308.	327032072.
	7	5135.	42654736.	** U06	7	3757.	33095002.	** UL7	7	1342.	32559440.
	8	5381.	42654736.	** U06	8	3790.	33095002.	** UL7	8	1342.	32559440.
	9	5436.	44662732.	** U06	9	3757.	33095002.	** UL7	9	1347.	3530836.
	10	5436.	44662732.	** U06	10	3757.	33095002.	** UL7	10	1347.	3530836.
UM1	1	3703.	19943230.	** XE2	1	7932.	13162916.	** UC2	1	6736.	97258116.
	2	3337.	29715038.	** XE2	2	7770.	10320220.	** UC2	2	5548.	30004834.
	3	3363.	29715038.	** XE2	3	7987.	113457168.	** UC2	3	5338.	41418328.
	4	3683.	29715038.	** XE2	4	8132.	113457168.	** UC2	4	4983.	37498458.
	5	3787.	26716654.	** XE2	5	8091.	123375440.	** UC2	5	4598.	31324760.
	6	3658.	26011664.	** XE2	6	7576.	123375440.	** UC2	6	4588.	31324760.
	7	3495.	24811008.	** XE2	7	7701.	100155558.	** UC2	7	4605.	31324760.
	8	3378.	24811008.	** XE2	8	7391.	86759662.	** UC2	8	4637.	3069792.
	9	3341.	23583210.	** XE2	9	7391.	86759662.	** UC2	9	4637.	3069792.
	10	3341.	23583210.	** XE2	10	7391.	86759662.	** UC2	10	4637.	3069792.

AGGREGATE TOTALS

AVG	MAD	MDS
1	7058.	73306608.
2	6166.	60366096.
3	5321.	60366096.
4	5226.	54574548.
5	5304.	55543572.
6	5040.	55543572.
7	5135.	55543572.
8	5381.	55543572.
9	5436.	55543572.
10	5436.	55543572.

COMPUTER OUTPUT THREE-ONE

Mean Absolute Deviation (in cubic feet)



Smoothing Constant (alpha)

COMPUTER OUTPUT THREE-TWO

PCD ALPHA	MADEV	MDEV SQ	PCD ALPHA	MADEV	MDEV SQ	PCD ALPHA	MADEV	MDEV SQ	PCD ALPHA	MADEV	MDEV SQ	MOD	ALPHA	MADEV	MDEV SQ	PCD ALPHA	MADEV	MDEV SQ
RA3	8501.	129705008.	1.00	4619.	35720772.	1.00	2137.	149777228.	1.00	1372.	149777228.	PJ3	1.00	1372.	149777228.	1.00	1372.	149777228.
	8433.	126001854.	0.99	4587.	334271840.	0.99	2127.	145775049.	0.99	1366.	145775049.		0.99	1366.	145775049.	0.99	1366.	145775049.
	8338.	126544544.	0.97	4574.	332984152.	0.97	2092.	143889410.	0.97	1355.	143889410.		0.97	1355.	143889410.	0.97	1355.	143889410.
	8332.	125439432.	0.95	4554.	327554566.	0.95	2077.	142033042.	0.95	1346.	142033042.		0.95	1346.	142033042.	0.95	1346.	142033042.
	8256.	122403952.	0.94	4521.	325244600.	0.94	2062.	140203042.	0.94	1340.	140203042.		0.94	1340.	140203042.	0.94	1340.	140203042.
	8117.	122473788.	0.93	4476.	322077760.	0.93	2048.	138477618.	0.93	1333.	138477618.		0.93	1333.	138477618.	0.93	1333.	138477618.
	8114.	120533728.	0.92	4448.	318677520.	0.92	2033.	136747618.	0.92	1327.	136747618.		0.92	1327.	136747618.	0.92	1327.	136747618.
	8114.	119472480.	0.91	4421.	316438080.	0.91	2005.	135512331.	0.91	1322.	135512331.		0.91	1322.	135512331.	0.91	1322.	135512331.
	8109.	117893280.	0.90	4414.	314231808.	0.90	1990.	133512331.	0.90	1316.	133512331.		0.90	1316.	133512331.	0.90	1316.	133512331.
	8090.	116933280.	0.89	4414.	310344472.	0.89	1974.	131957430.	0.89	1310.	131957430.		0.89	1310.	131957430.	0.89	1310.	131957430.
	8090.	116513280.	0.88	4431.	308344472.	0.88	1962.	130457430.	0.88	1304.	130457430.		0.88	1304.	130457430.	0.88	1304.	130457430.
	8090.	115332768.	0.87	4431.	304502720.	0.87	1950.	128957430.	0.87	1298.	128957430.		0.87	1298.	128957430.	0.87	1298.	128957430.
	8084.	114522264.	0.85	4439.	302800768.	0.85	1908.	127462470.	0.85	1288.	127462470.		0.85	1288.	127462470.	0.85	1288.	127462470.
	8084.	113742064.	0.84	4439.	300800768.	0.84	1892.	126247030.	0.84	1282.	126247030.		0.84	1282.	126247030.	0.84	1282.	126247030.
	7992.	112974444.	0.82	4354.	299014433.	0.82	1884.	125214970.	0.82	1268.	125214970.		0.82	1268.	125214970.	0.82	1268.	125214970.
	7899.	112224000.	0.81	4335.	297244233.	0.81	1869.	124079710.	0.81	1256.	124079710.		0.81	1256.	124079710.	0.81	1256.	124079710.
	7873.	111495376.	0.80	4326.	295480160.	0.80	1857.	122997970.	0.80	1245.	122997970.		0.80	1245.	122997970.	0.80	1245.	122997970.
	7844.	110774352.	0.78	4326.	293820160.	0.78	1835.	121944410.	0.78	1233.	121944410.		0.78	1233.	121944410.	0.78	1233.	121944410.
	7799.	110074352.	0.76	4299.	292152336.	0.76	1824.	120932550.	0.76	1224.	120932550.		0.76	1224.	120932550.	0.76	1224.	120932550.
	7773.	109391656.	0.75	4279.	288912276.	0.75	1814.	120025520.	0.75	1219.	120025520.		0.75	1219.	120025520.	0.75	1219.	120025520.
	7748.	108710008.	0.74	4266.	285800352.	0.74	1793.	119134112.	0.74	1215.	119134112.		0.74	1215.	119134112.	0.74	1215.	119134112.
	7697.	107440444.	0.73	4254.	284260976.	0.73	1782.	118262622.	0.73	1210.	118262622.		0.73	1210.	118262622.	0.73	1210.	118262622.
	7697.	106220336.	0.72	4254.	282600976.	0.72	1772.	117422622.	0.72	1205.	117422622.		0.72	1205.	117422622.	0.72	1205.	117422622.
	7646.	105623392.	0.71	4215.	281557760.	0.71	1752.	116633337.	0.71	1200.	116633337.		0.71	1200.	116633337.	0.71	1200.	116633337.
	7594.	104502400.	0.69	4188.	279544800.	0.69	1743.	115863337.	0.69	1199.	115863337.		0.69	1199.	115863337.	0.69	1199.	115863337.
	7567.	103496560.	0.68	4173.	277477200.	0.68	1735.	115115667.	0.68	1199.	115115667.		0.68	1199.	115115667.	0.68	1199.	115115667.
	7541.	102493076.	0.67	4158.	275444688.	0.67	1726.	114383337.	0.67	1197.	114383337.		0.67	1197.	114383337.	0.67	1197.	114383337.
	7447.	101493076.	0.65	4113.	273200000.	0.65	1712.	113674537.	0.65	1197.	113674537.		0.65	1197.	113674537.	0.65	1197.	113674537.
	7447.	101303312.	0.62	4110.	271953160.	0.62	1710.	112982270.	0.62	1197.	112982270.		0.62	1197.	112982270.	0.62	1197.	112982270.
	7394.	100575840.	0.61	4092.	269532076.	0.61	1709.	112320520.	0.61	1197.	112320520.		0.61	1197.	112320520.	0.61	1197.	112320520.
	7374.	99792224.	0.59	4052.	267230976.	0.59	1709.	111697970.	0.59	1197.	111697970.		0.59	1197.	111697970.	0.59	1197.	111697970.
	7374.	98792224.	0.57	4028.	265127760.	0.57	1710.	111094980.	0.57	1197.	111094980.		0.57	1197.	111094980.	0.57	1197.	111094980.
	7338.	98520040.	0.55	3989.	263081680.	0.55	1711.	110522970.	0.55	1197.	110522970.		0.55	1197.	110522970.	0.55	1197.	110522970.
	7338.	98220040.	0.53	3989.	261022096.	0.53	1715.	109994980.	0.53	1197.	109994980.		0.53	1197.	109994980.	0.53	1197.	109994980.
	7271.	97933336.	0.52	3937.	259333712.	0.52	1716.	109484980.	0.52	1197.	109484980.		0.52	1197.	109484980.	0.52	1197.	109484980.
	7250.	97638000.	0.50	3917.	257666360.	0.50	1726.	108994980.	0.50	1197.	108994980.		0.50	1197.	108994980.	0.50	1197.	108994980.
	7209.	97498872.	0.49	3899.	256132360.	0.49	1733.	108524980.	0.49	1197.	108524980.		0.49	1197.	108524980.	0.49	1197.	108524980.
	7194.	967442288.	0.48	3880.	254747976.	0.48	1747.	108074980.	0.48	1197.	108074980.		0.48	1197.	108074980.	0.48	1197.	108074980.
	7158.	96465136.	0.47	3844.	253474976.	0.47	1755.	107644980.	0.47	1197.	107644980.		0.47	1197.	107644980.	0.47	1197.	107644980.
	7124.	95941008.	0.46	3825.	252474976.	0.46	1764.	107234980.	0.46	1197.	107234980.		0.46	1197.	107234980.	0.46	1197.	107234980.
	7109.	95498256.	0.45	3825.	251744976.	0.45	1782.	106844980.	0.45	1197.	106844980.		0.45	1197.	106844980.	0.45	1197.	106844980.
	7058.	95097412.	0.44	3778.	251244976.	0.44	1792.	106474980.	0.44	1197.	106474980.		0.44	1197.	106474980.	0.44	1197.	106474980.
	7054.	94795452.	0.42	3778.	250844976.	0.42	1815.	106134980.	0.42	1197.	106134980.		0.42	1197.	106134980.	0.42	1197.	106134980.
	7043.	94460780.	0.40	3729.	250444976.	0.40	1842.	105824980.	0.40	1197.	105824980.		0.40	1197.	105824980.	0.40	1197.	105824980.
	7022.	94434480.	0.39	3672.	250144976.	0.39	1842.	105534980.	0.39	1197.	105534980.		0.39	1197.	105534980.	0.39	1197.	105534980.
	7021.	94434480.	0.37	3672.	250044976.	0.37	1877.	105254980.	0.37	1197.	105254980.		0.37	1197.	105254980.	0.37	1197.	105254980.
	7021.	94033176.	0.35	3665.	250044976.	0.35	1877.	104984980.	0.35	1197.	104984980.		0.35	1197.	104984980.	0.35	1197.	104984980.
	7021.	93033176.	0.33	3644.	249990720.	0.33	1920.	104734980.	0.33	1197.	104734980.		0.33	1197.	104734980.	0.33	1197.	104734980.
	7021.	92033176.	0.32	3632.	249990720.	0.32	1920.	104494980.	0.32	1197.	104494980.		0.32	1197.	104494980.	0.32	1197.	104494980.

COMPUTER OUTPUT THREE-THREE

TABLE OF AGGREGATE DEVIATIONS FOR ALL ALPHAS .01-.80

1.00	70654.	736637184.
0.99	70377.	730399744.
0.98	70109.	724290048.
0.97	69843.	718301696.
0.96	69585.	712430080.
0.95	69332.	706677248.
0.94	69080.	701039616.
0.93	68831.	695513856.
0.92	68582.	690097152.
0.91	68334.	684788480.
0.90	68091.	679587072.
0.89	67849.	674489344.
0.88	67607.	669492736.
0.87	67363.	664599040.
0.86	67120.	659803136.
0.85	66878.	655104000.
0.84	66634.	650502656.
0.83	66392.	645997568.
0.82	66153.	641583872.
0.81	65919.	637264384.
0.80	65693.	633036800.
0.79	65470.	628899584.
0.78	65252.	624851712.
0.77	65034.	620893440.
0.76	64817.	617023744.
0.75	64599.	613240320.
0.74	64382.	609544704.
0.73	64169.	605935104.
0.72	63955.	602411520.
0.71	63741.	598973440.
0.70	63527.	595620352.
0.69	63320.	592351488.
0.68	63118.	589167872.
0.67	62921.	586068224.
0.66	62727.	583053056.
0.65	62535.	580122368.
0.64	62352.	577276160.
0.63	62174.	574514176.
0.62	61998.	571837184.
0.61	61826.	569245440.
0.60	61665.	566738944.
0.59	61511.	564319488.
0.58	61363.	561986560.
0.57	61217.	559740672.
0.56	61071.	557583104.
0.55	60929.	555515392.
0.54	60785.	553538048.
0.53	60649.	551652352.
0.52	60518.	549859840.
0.51	60394.	548163072.
0.50	60276.	546563328.
0.49	60165.	545062656.
0.48	60060.	543662848.
0.47	59959.	542367488.
0.46	59873.	541178368.
0.45	59788.	540100352.
0.44	59712.	539136256.
0.43	59643.	538288996.
0.42	59582.	537564672.
0.41	59527.	536968192.
0.40	59477.	536504832.
0.39	59437.	536179968.
0.38	59409.	536002560.
0.37	59388.	535979264.
0.36	59367.	536119552.
0.35	59402.	536432128.
0.34	59424.	536930304.
0.33	59461.	537623296.
0.32	59505.	538528000.

COMPUTER OUTPUT FOUR-ONE

Mean Absolute Deviation (in cubic feet)



Smoothing Constant (alpha)

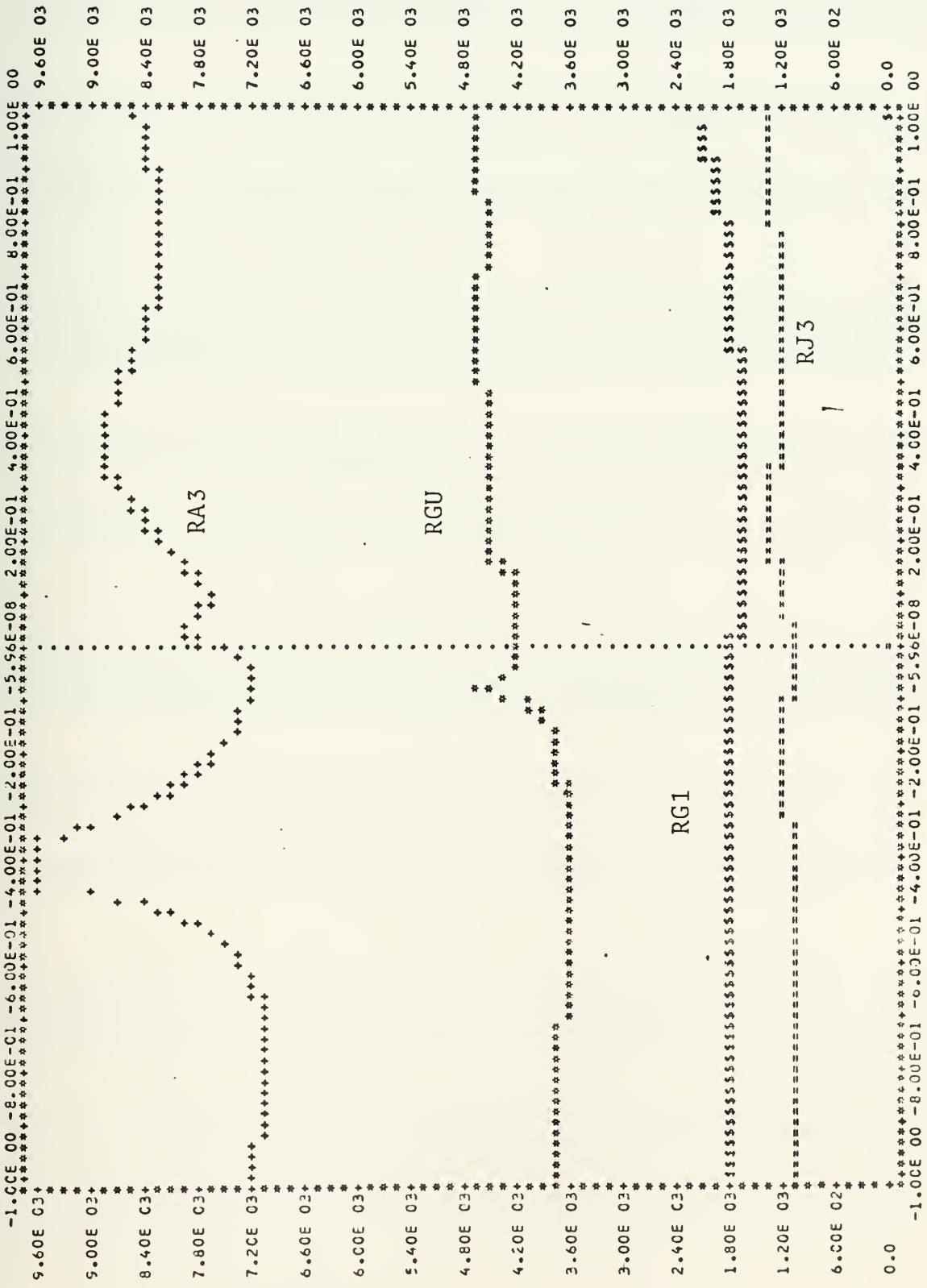
COMPUTER OUTPUT FOUR-THREE

TABLE CF AGGREGATE DEVIATIONS FOR ALL ALPHAS

1.00	118467.	2101308416.
0.99	117072.	2049801728.
0.98	115695.	2000065024.
0.97	114331.	1952017408.
0.96	112984.	1905584384.
0.95	111655.	1860698624.
0.94	110342.	1817293056.
0.93	109076.	1775303424.
0.92	107855.	1734674176.
0.91	106647.	1695347968.
0.90	105467.	1657269760.
0.89	104315.	1620392448.
0.88	103180.	1584663552.
0.87	102075.	1550044928.
0.86	100982.	1516489472.
0.85	99902.	1483955968.
0.84	98834.	1452407808.
0.83	97789.	1421804544.
0.82	96763.	1392116736.
0.81	95766.	1363305216.
0.80	94803.	1335342592.
0.79	93866.	1308194816.
0.78	92932.	1281838336.
0.77	92005.	1256241920.
0.76	91083.	1231379712.
0.75	90166.	1207229696.
0.74	89262.	1183765248.
0.73	88388.	1160964096.
0.72	87540.	1138805504.
0.71	86729.	1117269504.
0.70	85948.	1096335872.
0.69	85188.	1075986176.
0.68	84453.	1056201984.
0.67	83765.	1036966912.
0.66	83084.	1018264832.
0.65	82419.	1000078592.
0.64	81775.	982395648.
0.63	81141.	965200384.
0.62	80502.	948480000.
0.61	79859.	932221440.
0.60	79219.	916412928.
0.59	78581.	901042176.
0.58	77959.	886095104.
0.57	77368.	871566592.
0.56	76803.	857441792.
0.55	76237.	843713024.
0.54	75679.	830370048.
0.53	75125.	817404416.
0.52	74571.	804806656.
0.51	74029.	792569088.
0.50	73495.	780682496.
0.49	72962.	769141248.
0.48	72429.	757939456.
0.47	71901.	747066368.
0.46	71388.	736519168.
0.45	70871.	726288896.
0.44	70363.	716374784.
0.43	69850.	706766336.
0.42	69335.	697462016.
0.41	68835.	688456448.
0.40	68339.	679745536.
0.39	67840.	671324928.
0.38	67356.	663196672.
0.37	66887.	655353856.
0.36	66416.	647796736.
0.35	65952.	640525312.
0.34	65493.	633539584.
0.33	65042.	626838784.
0.32	64616.	620430080.

COMPUTER OUTPUT FIVE-ONE

Mean Absolute Deviation (in cubic feet)



Smoothing Constant (gamma)

COMPUTER OUTPUT FIVE-TWO

	PCC	GAM	MACEV	MDEVSC	RKU	GAM	MACEV	MDEVSC	RG1	GAM	MACEV	MDEVSC	PCD	GAM	PCD	RJ3	GAM	MACEV	MDEVSC	MOEVSQ	Y
	00	00	19	37	00	00	40	33	*	00	0	14	*	00	*	00	1372	4582	9008	72	
	00	00	27	36	00	00	40	33	*	00	21	45	*	00	*	00	1365	4571	9033	72	
	00	00	30	36	00	00	40	33	*	00	20	44	*	00	*	00	1358	4560	9080	72	
	00	00	33	35	00	00	40	33	*	00	20	44	*	00	*	00	1350	4548	9127	72	
	00	00	34	35	00	00	40	33	*	00	20	44	*	00	*	00	1343	4537	9174	72	
	00	00	35	34	00	00	40	33	*	00	20	44	*	00	*	00	1335	4525	9221	72	
	00	00	36	33	00	00	40	33	*	00	20	44	*	00	*	00	1328	4513	9268	72	
	00	00	37	33	00	00	40	33	*	00	20	44	*	00	*	00	1320	4501	9315	72	
	00	00	38	33	00	00	40	33	*	00	20	44	*	00	*	00	1312	4489	9362	72	
	00	00	39	33	00	00	40	33	*	00	20	44	*	00	*	00	1304	4477	9409	72	
	00	00	40	33	00	00	40	33	*	00	20	44	*	00	*	00	1296	4465	9456	72	
	00	00	41	33	00	00	40	33	*	00	20	44	*	00	*	00	1288	4453	9503	72	
	00	00	42	33	00	00	40	33	*	00	20	44	*	00	*	00	1280	4441	9550	72	
	00	00	43	33	00	00	40	33	*	00	20	44	*	00	*	00	1272	4429	9597	72	
	00	00	44	33	00	00	40	33	*	00	20	44	*	00	*	00	1264	4417	9644	72	
	00	00	45	33	00	00	40	33	*	00	20	44	*	00	*	00	1256	4405	9691	72	
	00	00	46	33	00	00	40	33	*	00	20	44	*	00	*	00	1248	4393	9738	72	
	00	00	47	33	00	00	40	33	*	00	20	44	*	00	*	00	1240	4381	9785	72	
	00	00	48	33	00	00	40	33	*	00	20	44	*	00	*	00	1232	4369	9832	72	
	00	00	49	33	00	00	40	33	*	00	20	44	*	00	*	00	1224	4357	9879	72	
	00	00	50	33	00	00	40	33	*	00	20	44	*	00	*	00	1216	4345	9926	72	
	00	00	51	33	00	00	40	33	*	00	20	44	*	00	*	00	1208	4333	9973	72	
	00	00	52	33	00	00	40	33	*	00	20	44	*	00	*	00	1200	4321	10000	72	
	00	00	53	33	00	00	40	33	*	00	20	44	*	00	*	00	1192	4309		72	
	00	00	54	33	00	00	40	33	*	00	20	44	*	00	*	00	1184	4297		72	
	00	00	55	33	00	00	40	33	*	00	20	44	*	00	*	00	1176	4285		72	
	00	00	56	33	00	00	40	33	*	00	20	44	*	00	*	00	1168	4273		72	
	00	00	57	33	00	00	40	33	*	00	20	44	*	00	*	00	1160	4261		72	
	00	00	58	33	00	00	40	33	*	00	20	44	*	00	*	00	1152	4249		72	
	00	00	59	33	00	00	40	33	*	00	20	44	*	00	*	00	1144	4237		72	
	00	00	60	33	00	00	40	33	*	00	20	44	*	00	*	00	1136	4225		72	
	00	00	61	33	00	00	40	33	*	00	20	44	*	00	*	00	1128	4213		72	
	00	00	62	33	00	00	40	33	*	00	20	44	*	00	*	00	1120	4201		72	
	00	00	63	33	00	00	40	33	*	00	20	44	*	00	*	00	1112	4189		72	
	00	00	64	33	00	00	40	33	*	00	20	44	*	00	*	00	1104	4177		72	
	00	00	65	33	00	00	40	33	*	00	20	44	*	00	*	00	1096	4165		72	
	00	00	66	33	00	00	40	33	*	00	20	44	*	00	*	00	1088	4153		72	
	00	00	67	33	00	00	40	33	*	00	20	44	*	00	*	00	1080	4141		72	
	00	00	68	33	00	00	40	33	*	00	20	44	*	00	*	00	1072	4129		72	
	00	00	69	33	00	00	40	33	*	00	20	44	*	00	*	00	1064	4117		72	
	00	00	70	33	00	00	40	33	*	00	20	44	*	00	*	00	1056	4105		72	
	00	00	71	33	00	00	40	33	*	00	20	44	*	00	*	00	1048	4093		72	
	00	00	72	33	00	00	40	33	*	00	20	44	*	00	*	00	1040	4081		72	
	00	00	73	33	00	00	40	33	*	00	20	44	*	00	*	00	1032	4069		72	
	00	00	74	33	00	00	40	33	*	00	20	44	*	00	*	00	1024	4057		72	
	00	00	75	33	00	00	40	33	*	00	20	44	*	00	*	00	1016	4045		72	
	00	00	76	33	00	00	40	33	*	00	20	44	*	00	*	00	1008	4033		72	
	00	00	77	33	00	00	40	33	*	00	20	44	*	00	*	00	1000	4021		72	
	00	00	78	33	00	00	40	33	*	00	20	44	*	00	*	00	992	4009		72	
	00	00	79	33	00	00	40	33	*	00	20	44	*	00	*	00	984	3997		72	
	00	00	80	33	00	00	40	33	*	00	20	44	*	00	*	00	976	3985		72	
	00	00	81	33	00	00	40	33	*	00	20	44	*	00	*	00	968	3973		72	
	00	00	82	33	00	00	40	33	*	00	20	44	*	00	*	00	960	3961		72	
	00	00	83	33	00	00	40	33	*	00	20	44	*	00	*	00	952	3949		72	
	00	00	84	33	00	00	40	33	*	00	20	44	*	00	*	00	944	3937		72	
	00	00	85	33	00	00	40	33	*	00	20	44	*	00	*	00	936	3925		72	
	00	00	86	33	00	00	40	33	*	00	20	44	*	00	*	00	928	3913		72	
	00	00	87	33	00	00	40	33	*	00	20	44	*	00	*	00	920	3901		72	
	00	00	88	33	00	00	40	33	*	00	20	44	*	00	*	00	912	3889		72	
	00	00	89	33	00	00	40	33	*	00	20	44	*	00	*	00	904	3877		72	
	00	00	90	33	00	00	40	33	*	00	20	44	*	00	*	00	896	3865		72	
	00	00	91	33	00	00	40	33	*	00	20	44	*	00	*	00	888	3853		72	
	00	00	92	33	00	00	40	33	*	00	20	44	*	00	*	00	880	3841		72	
	00	00	93	33	00	00	40	33	*	00	20	44	*	00	*	00	872	3829		72	
	00	00	94	33	00	00	40	33	*	00	20	44	*	00	*	00	864	3817		72	
	00	00	95	33	00	00	40	33	*	00	20	44	*	00	*	00	856	3805		72	
	00	00	96	33	00	00	40	33	*	00	20	44	*	00	*	00	848	3793		72	
	00	00	97	33	00	00	40	33	*	00	20	44	*	00	*	00	840	3781		72	
	00	00	98	33	00	00	40	33	*	00	20	44	*	00	*	00	832	3769		72	
	00	00	99	33	00	00	40	33	*	00	20	44	*	00	*	00	824	3757		72	
	00	00	100	33	00	00	40	33	*	00	20	44	*	00	*	00	816	3745		72	

COMPUTER OUTPUT FIVE-THREE

Aggregate Mean Absolute Deviation (in cubic feet)



Smoothing Constant (gamma)

COMPUTER PROGRAM ONE

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C THIS PROGRAM COMPUTES THE FOLLOWING STATISTICAL INFORMATION FOR ALL PODS
C 1) OLS REGRESSION INTERCEPT AND SLOPE (AM AND BM)
C 2) STANDARD ERROR OF THE ESTIMATE (SM)
C 3) COEFFICIENT OF DETERMINATION (RM)
C 4) DURBIN-WATSON D-STATISTIC (DM)
C 5) THE MEAN AND BIWEEKLY INTERVALS OF TOTAL VOLUMES, SHIPMENTS OR WEIGHTS.
C FOR IMPLICIT INTEGER*4 (E-P)
1 DIMENSION POD(157),W(52),V(3,52),V1(52),Z1(52)
2 DIMENSION W21(26),V21(26),Z21(26),W22(25),V22(25),Z22(25)
3 DIMENSION AM(157,3),BM(157,3),SM(157,3),RM(157,3),DM(157,3)
4 DATA E/32/,F/26/,G/25/,O/157/
1 FORMAT(A3,4A4)
2 FURMA(T,ITABLE (NO.) OF STATISTICAL DATA FOR SELECTED PODS USING WEEKLY
3 TOTAL SHIPMENTS (NO.) DATA)
3 FORMAT(ITABLE OF STATISTICAL DATA FOR SELECTED PODS USING WEEKLY
4 TOTAL VOLUME (CU. FT.) DATA)
4 FORMAT(ITABLE OF STATISTICAL DATA FOR SELECTED PODS USING WEEKLY
5 TOTAL WEIGHT (LBS.) DATA)
5 FORMAT(OPUD INTERVAL START INTERCEPT SLOPE STD.ERR. R
1-SQUARE D-STAT OBS. MEANING)
6 FORMAT('0',A3,I6,I7,F12.0,E14.5,F10.1,2F11.5,I6,4X,A4)
7 FORMAT('4X',I6,I7,F12.0,E14.5,F10.1,2F11.5,I6,4X,A4)
8 FORMAT('1',)
DO 70 I=1,0
C READ DATA FOR A POD.
DO 10 J=1,E
DO 10 J=1,E
C LET SHIPMENTS=V(I,J), VOLUME=V(2,J), WEIGHT=V(3,J)
READ(14,1) POD(I),W(J),(V(M,J),M=1,3)
10 CONTINUE
C SET LEVEL OF M FOR THE MEASURE TO BE TESTED (M=2 FOR VOLUME).
M=2
C COMPUTE STATISTICS AND MEANING FOR WEEKLY INTERVALS.
DO 20 J=1,E
V1(J)=V(M,J)
20 CONTINUE
K=E
CALL LEASG2(W,V1,Z1,K,AM(I,1),BM(I,1),SM(I,1),RM(I,1),DM(I,1))
CALL DMNNG(DM(I,1),K,MNG(I,1))
C COMPUTE STATISTICS AND MEANING FOR BIWEEKLY INTERVALS STARTING IN WEEK 1.
DO 30 I=1,E/2
IF(J+1.GT.E) GO TO 32
L=(J+1)/2
W21(L)=V(M,J)
V21(L)=V(M,J)+V(M,J+1)
31 CONTINUE
K=F

```



```

32 CALL LEASQ2(W21, V21, Z21, K, AM(I, 2), BM(I, 2), SM(I, 2), RM(I, 2), DM(I, 2))
   CALL DMNING(DM(I, 2), K, MNG(I, 2))
C COMPUTE STATISTICS AND MEANING FOR BIWEEKLY INTERVALS STARTING IN WEEK 2.
40 DO 41 J=2, E, 2
   IF(J+1.GT.E) GO TO 42
   L=(J+1)/2
   W22(L)=FLOAT(L)
   V22(L)=V(M, J)+V(M, J+1)
41 CONTINUE
   K=G
42 CALL LEASQ2(W22, V22, Z22, K, AM(I, 3), BM(I, 3), SM(I, 3), RM(I, 3), DM(I, 3))
   CALL DMNING(DM(I, 3), K, MNG(I, 3))
70 CONTINUE
C PRINT TABLE HEADINGS FOR MEASURE TESTED.
   IF(M.EQ.1) WRITE(6, 2)
   IF(M.EQ.2) WRITE(6, 3)
   IF(M.EQ.3) WRITE(6, 4)
   IF(M.EQ.4) WRITE(6, 5)
C PRINT TABLE OF STATISTICS AND MEANINGS FOR ALL PODS FOR THE MEASURE TESTED.
   N=0
   N1=1
   N2=2
   DO 100 I=1, 0
     N=N+1
     IF(N.GE.20) GO TO 98
     GO TO 99
98 WRITE(6, 8)
   WRITE(6, 5)
   N=1
99 K=E
   WRITE(6, 6) POD(I), N1, N1, AM(I, 1), BM(I, 1), SM(I, 1), RM(I, 1), DM(I, 1), K,
1 MNG(I, 1)
   K=F
   WRITE(6, 7) N2, N1, AM(I, 2), BM(I, 2), SM(I, 2), RM(I, 2), DM(I, 2), K,
1 MNG(I, 2)
   K=G
   WRITE(6, 7) N2, N2, AM(I, 3), BM(I, 3), SM(I, 3), RM(I, 3), DM(I, 3), K,
1 MNG(I, 3)
100 CONTINUE
   STOP
   END

```



```

SUBROUTINE LEASQ2(X,Y,Z,N,A,B,S,RSQ,D)
C THIS SUBROUTINE COMPUTES STATISTICAL INFORMATION DERIVED FROM AN ORDINARY
C LEAST SQUARES REGRESSION, INCLUDING INTERCEPT(A), SLOPE (B), STANDARD ERROR
C OF THE ESTIMATE (S), COEFFICIENT OF DETERMINATION (RSQ), AND THE DURBIN-WATSON
C D-STATISTIC OF SERIAL CORRELATION (D).
C DIMENSION X(N), Y(N), Z(N)
C INITIALIZE WORKING VARIABLES.
SUMX=0.
SUMY=0.
SIGXY=0.
SIGXSQ=0.
SIGYSQ=0.
C COMPUTE THE SLOPE AND INTERCEPT OF THE OLS REGRESSION.
DO 1 M=1,N
SUMX=SUMX+X(M)
SUMY=SUMY+Y(M)
SIGXY=SIGXY+X(M)*Y(M)**2.
SIGXSQ=SIGXSQ+(ABS(X(M)))**2.
SIGYSQ=SIGYSQ+(ABS(Y(M)))**2.
1 CONTINUE
XBAR=SUMX/FLOAT(N)
YBAR=SUMY/FLOAT(N)
B1=SIGXY-(N*XBAR*YBAR)
B2=SIGXSQ-(N*(XBAR)**2.)
IF(B2.EQ.0.) GO TO 10
B=B1/B2
GO TO 11
10 B=0.
11 A=YBAR-B*XBAR
C COMPUTE THE STANDARD ERROR OF THE ESTIMATE.
S1=SIGYSQ-A*SUMY-B*SIGXY
S2=FLOAT(N-2)
IF(S2.EQ.0.) GO TO 20
S=SQRT((ABS(S1/S2)))
GO TO 21
20 S=0.
C COMPUTE THE COEFFICIENT OF DETERMINATION.
21 R1=A*SUMY+B*SIGXY-FLOAT(N)*(ABS(YBAR)**2.)
R2=SIGYSQ-FLOAT(N)*(ABS(YBAR)**2.)
IF(R2.EQ.0.) GO TO 30
RSQ=R1/R2
GO TO 31
30 RSQ=0.
31 SIGZSQ=0.
C ZERO THE VECTOR OF RESIDUALS.
DO 3 M=1,N

```



```

Z(M)=0.
3 CONTINUE
C COMPUTE A VECTOR OF RESIDUALS AROUND THE REGRESSION LINE.
DO 2 M=1,N
Z(M)=A+B*X(M)-Y(M)
C SUM THE SQUARED RESIDUALS AND RESIDUAL DIFFERENCES.
SIGZSQ=SIGZSQ+(ABS(Z(M)))**2.
IF (M.LE.1) GO TO 2
SIGZMZ=SIGZMZ+(ABS(Z(M)-Z(M-1)))**2.
2 CONTINUE
C COMPUTE THE DURBIN-WATSON D-STATISTIC.
IF(SIGZSQ.EQ.0.) GO TO 40
D=SIGZMZ/SIGZSQ
GO TO 41
40 D=0.
41 RETURN
END

```

```

SUBROUTINE DMNNG(D,K,MNG)
C THIS SUBROUTINE DETERMINES THE MEANING OF THE D-STATISTIC FOR K OBSERVATIONS
C AND 1 INDEPENDENT VARIABLE.
INTEGER*4 POSI
DATA POSI/'POSI', NEGA/'NEGA', NONE/'NONE', INCN/'INCN'//
C D-STAT LEVELS FOR 52 OBSERVATIONS
DL1=1.512
DU1=1.594
D4U1=2.406
D4L1=2.488
C D-STAT LEVELS FOR 26 OBSERVATIONS
DL2=1.30
DU2=1.46
D4U2=2.54
D4L2=2.70
C D-STAT LEVELS FOR 25 OBSERVATIONS
DL3=1.29
DU3=1.45
D4U3=2.55
D4L3=2.71
C SELECT SET OF LEVELS TO BE USED BASED ON THE NUMBER OF OBSERVATIONS.
IF(K.EQ.26) GO TO 10
IF(K.EQ.25) GO TO 20

```


C PROCEDURE FOR DETERMINING MEANING OF D-STAT FOR SAMPLE WITH 52 OBSERVATIONS.

```
IF(D.GT.DL1) GO TO 1
MNG=POSI
RETURN
1 IF(D.GE.DU1) GO TO 2
MNG=INCN
RETURN
2 IF(D.GT.D4U1) GO TO 3
MNG=NONE
RETURN
3 IF(D.GE.D4L1) GO TO 4
MNG=INCN
RETURN
4 MNG=NEGA
RETURN
```

C PROCEDURE FOR DETERMINING MEANING OF D-STAT FOR SAMPLE WITH 26 OBSERVATIONS.

```
10 IF(D.GT.DL2) GO TO 11
MNG=POSI
RETURN
11 IF(D.GE.DU2) GO TO 12
MNG=INCN
RETURN
12 IF(D.GT.D4U2) GO TO 13
MNG=NONE
RETURN
13 IF(D.GT.D4L2) GO TO 14
MNG=INCN
RETURN
14 MNG=NEGA
RETURN
```

C PROCEDURE FOR DETERMINING MEANING OF D-STAT FOR SAMPLE WITH 25 OBSERVATIONS.

```
20 IF(D.GT.DL3) GO TO 21
MNG=POSI
RETURN
21 IF(D.GE.DU3) GO TO 22
MNG=INCN
RETURN
22 IF(D.GT.D4U3) GO TO 23
MNG=NONE
RETURN
23 IF(D.GE.D4L3) GO TO 24
MNG=INCN
RETURN
24 MNG=NEGA
RETURN
END
```


COMPUTER PROGRAM TWO

```

C THIS PROGRAM COMPUTES (N WEEK) MOVING AVERAGES FOR 1 TO 10 (NAVG) WEEK
C INTERVALS OF WEEKLY TOTAL VOLUMES (VOL) FOR 16 (NPOD) PODS, USES THE AVERAGES
C TO FORECAST (FCST) TO A SPECIFIED TIME HORIZON (NHORIZ), AND COMPUTES
C DEVIATION STATISTICS FOR THE FORECAST (MADEV = MEAN ABSOLUTE DEVIATION,
C MDEVSQ = MEAN DEVIATION SQUARED). DEVIATION STATISTICS FOR THE VARIOUS
C INTERVALS ARE AGGREGATED THRU ALL PODS (TMAD AND TMADSQ).
C ***** 1 WEEK HORIZON *****
C INTEGER POD
C REAL MADEV, MDEVSQ
C DIMENSION POD(16), VOL(52), DEV(52), DEVSQ(52), FCST(52)
C DIMENSION MADEV(16,10), MDEVSQ(16,10)
C DIMENSION TMAD(10), TMADSQ(10)
C DATA TMAD/10*0./, NPOD/16/, TMADSQ/10*0./
C DATA K/52/, NHORIZ/1/, NAVG/10/
C FORMAT('TABLE OF DEVIATION FOR PODS USING VARIOUS DURATIONS OF MO
1 1 VING AVERAGES')
2 3 FORMAT('0',4('POD',AVG,MAD,MDS,**'))
4 5 FORMAT('1X',4('A3',15,F8.0,F13.0,**'))
6 6 FORMAT('1X',7('/',,AGGREGATE TOTALS',/,,'AVG,MAD,MDS'))
7 7 FORMAT('1X',13,F8.0,F13.0)
C DO 19 N=1, NPOD
C READ K WEEKLY TOTAL VOLUMES OBSERVED FOR A POD.
C DO 14 I=1,K
C READ(5,1) POD(N), VOL(I)
14 C CONTINUE
C SET THE MOVING AVERAGE INTERVAL TO BE USED.
C DO 19 L=1,NAVG
C ZERO AND INITIALIZE WORKING VARIABLES.
C DO 15 I=1,K
C DEV(I)=0.
C DEVSQ(I)=0.
C FCST(I)=0.
15 C CONTINUE
C TDEV=0.
C TDEVSQ=0.
C JJ=0
C NEEK=L
C KEND=K+1-NHORIZ
C START THE FORECAST GENERATION PROCEDURE.
C DO 18 I=NAVG,KEND
C SKIP THE DEVIATION CALCULATIONS IF THIS IS THE FIRST SET OF OBSERVATIONS AS
C THE FIRST FORECAST IS NOT YET COMPUTED.
C IF(I.EQ.NEEK) GO TO 11
C CALCULATE THE DEVIATIONS FROM THE FORECAST FOR THE CURRENT PERIOD.
C APPLY THE CURRENT FORECAST TO NHORIZ PERIODS.
C DO 16 M=1,NHORIZ

```



```

J=I-1+M
DEV(I)=DEV(I)+FCST(I)-VOL(J)
16 CONTINUE
DEV(I)=ABS(DEV(I))/FLOAT(NHORIZ))
DEVSQ(I)=DEV(I)**2.
TDEV=TDEV+DEV(I)
TDEVSQ=TDEVSQ+DEVSQ(I)
JJ=JJ+1
C SKIP THE FORECAST CALCULATION THAT WOULD APPLY TO PERIOD K+1.
IF(I.EQ.END) GO TO 18
C CALCULATE THE MOVING AVERAGE AND FORECAST FOR THE NEXT PERIOD.
11 DO 17 M=1,NWEEK
J=I+1-M
FCST(I+1)=FCST(I+1)+VOL(J)
17 CONTINUE
FCST(I+1)=FCST(I+1)/FLOAT(NWEEK)
18 CONTINUE
C COMPUTE THE DEVIATION STATISTICS FOR THE INTERVAL AND POD.
MADEV(N,L)=TDEV/FLOAT(JJ)
MDEVSQ(N,L)=TDEVSQ/FLOAT(JJ)
19 CONTINUE
C AGGREGATE THE DEVIATION STATISTICS FOR THE MOVING AVERAGE INTERVAL.
DO 20 L=1,NAVG
DO 20 N=1,NPOD
TMADSQ(L)=TMADSQ(L)+MDEVSQ(N,L)
TMAD(L)=TMAD(L)+MADEV(N,L)
20 PRINT OUT TABLES OF AVERAGE WEEKLY DEVIATIONS FOR ALL MOVING AVERAGE
INTERVALS COMPUTED FOR EACH POD.
WRITE(6,2)
WRITE(6,3)
MPOD=NPOD/4
DO 32 M=1,MPOD
L=(M-1)*4+1
LL=M*4
I=1
WRITE(6,4) (POD(N),I,MADEV(N,I),MDEVSQ(N,I),N=L,LL)
DO 32 I=2,NAVG
WRITE(6,5) (I,MADEV(N,I),MDEVSQ(N,I),N=L,LL)
32 CONTINUE
C PRINT OUT THE AGGREGATE DEVIATION STATISTICS FOR ALL INTERVALS COMPUTED.
WRITE(6,6)
WRITE(6,7) (L,TMAD(L),TMADSQ(L),L=1,NAVG)
WRITE(6,8)
8 FORMAT('I')
STOP
END

```


COMPUTER PROGRAM THREE

```

C THIS PROGRAM COMPUTES FORECASTS (FCST) TO A SPECIFIED TIME HORIZON (NHORIZ)
C USING SIMPLE EXPONENTIALLY WEIGHTED AVERAGES FOR VARYING SMOOTHING COEFFIC-
C IENTS (ALFA) FOR 16 (NPOD) PODS. IT ALSO COMPUTES DEVIATION STATISTICS FOR
C THE FORECAST (MADEV = MEAN ABSOLUTE DEVIATION, MDEVSQ = MEAN DEVIATION
C SQUARED). DEVIATION STATISTICS FOR THE VARIOUS ALFA LEVELS ARE AGGREGATED
C THRU ALL PODS (TMAD AND TMADSQ). PROVISIONS FOR PLOTTING RESULTS ARE
C INCLUDED.
C ***** ONE (1) WEEK HORIZON*****
C INTEGER POD
C REAL MADLV, MDEVSQ
C DIMENSION VOL(52), DEV(52), DEVSQ(52), FCST(52), FCSTAV(52)
C DIMENSION ALFA(11), MADEV(16,11), MDEVSQ(16,11), POD(16)
C DIMENSION X(101), Y(101,4), TMAD(11), TMADSQ(11)
C DATA TMAD/11*0./, NPOD/16/, NALFA/11/
C DATA ALFSTP/100./, NHORIZ/1/
C 1 FORMAT(I3) 27X,F10.0)
C 2 FORMAT(A3,4('POD ALPHA MADEV MDEVSQ * '))
C 3 FORMAT('0',4(A3,F5.2,F8.0,F13.0,' * '))
C 4 FORMAT('1X,4(3X,F5.2,F8.0,F13.0,' * '))
C 5 FORMAT('1X,4(3X, F5.2,F8.0,F13.0,F20.0)
C 6 FORMAT('1X, F5.2, F12.0,F20.0)
C 7 READ A NUMBER (NA) TO INITIALIZE THE COMPUTATION OF ALFAS BY 100THS (ALFSTP)
C OVER: A DESIRED RANGE (NALFA).
C 9 READ(5,1) NA
C DO 9 L=1,NALFA
C ALFA(L)=(FLOAT(NA-L))/ALFSTP
C CONTINUE
C 10 DO 19 N=1,NPOD
C READ K WEEKLY TOTAL VOLUMES OBSERVED FOR A POD.
C DO 12 I=1,K POD(N), VOL(I)
C READ(5,2)
C CONTINUE
C 12 SET THE SMOOTHING CONSTANT LEVEL (ALFA) TO BE USED.
C DO 19 L=1,NALFA
C ZER0 AND INITIALIZE WORKING VARIABLES.
C DO 13 I=1,K
C DEV(I)=0.
C DEVSQ(I)=0.
C FCST(I)=0.
C FCSTAV(I)=0.
C CONTINUE
C 13 TDEVSQ=0.
C TDEVSQ=0.
C JJ=0
C ALFA=1.-ALFA(L)
C FCSTAV(I)=VOL(I)

```



```

C START THE FORECAST GENERATION PROCEDURE.
C DO 16 I=2,K
C SKIP THE DEVIATION CALCULATIONS IF THIS IS THE FIRST SET OF OBSERVATIONS AS
C THE FIRST FORECAST IS NOT YET COMPUTED.
C IF(I.EQ.2) GO TO 15
C CALCULATE THE DEVIATIONS FROM THE FORECAST FOR THE CURRENT PERIOD.
C APPLY THE CURRENT FORECAST TO NHORIZ PERIODS.
DO 14 M=1,NHORIZ
  J=I+NHORIZ-M
  DEV(I)=DEV(I)+FCST(I)-VOL(J)
14 CONTINUE
  DEV(I)=ABS(DEV(I)/FLOAT(NHORIZ))
  DEVSQ(I)=DEV(I)**2.
  TDEV=TDEV + DEV(I)
  TDEVSQ = TDEVSQ + DEVSQ(I)
  JJ=JJ+1
C SKIP THE FORECAST CALCULATION THAT WOULD APPLY THRU PERIOD K+1.
15 IF(I-1+NHORIZ.EQ.K) GO TO 17
C CALCULATE THE EXPONENTIALLY WEIGHTED AVERAGE (FCSTAV) AND FORECAST (FCST)
C FOR THE NEXT PERIOD.
  FCSTAV(I)=ALFA(L)*VOL(I) + ALFA*FCSTAV(I-1)
  FCST(I+1)=FCSTAV(I)
16 CONTINUE
C COMPUTE THE DEVIATION STATISTICS FOR THE POD AT THIS ALFA LEVEL.
17 MADEV(N,L)=TDEV/FLOAT(JJ)
  MDEVSQ(N,L)=TDEVSQ/FLOAT(JJ)
  GO TO 19
18 MADEV(N,L)=0.
  MDEVSQ(N,L)=0.
19 CONTINUE
C AGGREGATE THE DEVIATION STATISTICS FOR THE ALFA LEVEL INTERVALS.
DO 70 N=1,NPOD
  DO 70 L=1,NALFA
    TMAD(L)=TMAD(L)+MADEV(N,L)
    TMADSQ(L)=TMADSQ(L)+MDEVSQ(N,L)
70 CONTINUE
C ** INCLUDE AT THIS POINT A ROUTINE TO CALL FOR PLOTS OF ALFA LEVELS VS.
C EITHER DEVIATION STATISTIC FOR A POD. ORIGINALLY THIS THEISIS USED THE
C SUBROUTINE OSPLT AVAILABLE AT THE W. R. CHURCH COMPUTER CENTER, NAVAL
C POSTGRADUATE SCHOOL, MONTEREY, CAL. **
C ROUTINE FOR PLOTTING ALPHA LEVELS VS PODS
  SET NX = NALFA OR NGAMMA DEPENDING OF FORECASTING METHOD
  NX=NALFA
  M=0
50 M=M+1
  IF(M.GT.4) GO TO 20

```



```

DO 60 I=11, NX
J=NX+1-I
X(J)=ALFA(I)
DC 60 N=1, 4
L=(M-1)*4+N
Y(J,N)=MADEV(L,I)
60 CONTINUE
NDIM=101
N=NDIM
NCUR=4
ISCALE=1
XLFT=-.1
XRT=.9
YLO=0.
YHI=9600.
CALL DSPLOT(X,Y,N,NDIM,NCUR,ISCALE,XLFT,XRT,YLO,YHI)
C PRINT OUT TABLES OF AVERAGE WEEKLY DEVIATIONS FOR ALL ALFA LEVEL INTERVALS
C COMPUTED FOR EACH POD.
WRITE(6,3)
L=(M-1)*4+1
LL=M*4
WRITE(6,4) (POD(N),ALFA(1),MADEV(N,1),MDEVSQ(N,1),N=L,LL)
DO 61 I=2, NALFA
IF(I.EQ.70) WRITE(6,3)
WRITE(6,5) (ALFA(I),MADEV(N,I),MDEVSQ(N,I),N=L,LL)
61 CONTINUE
GO TO 50
20 CONTINUE
C PRINT OUT AGGREGATE DEVIATION STATISTICS FOR ALL ALFA LEVEL INTERVALS
C COMPUTED.
WRITE(6,6)
DO 25 I=1, NALFA
IF(I.EQ.70) WRITE(6,6)
WRITE(6,7) ALFA(I), TMAD(I), TMADSQ(I)
25 CONTINUE
STOP
END

```


COMPUTER PROGRAM FOUR

```

C THIS PROGRAM COMPUTES FORECASTS (FCST) TO A SPECIFIED TIME HORIZON (NHORIZ)
C USING EXPONENTIALLY WEIGHTED AVERAGES WITH ADJUSTMENTS FOR TREND EFFECTS
C FOR VARYING LEVELS OF SMOOTHING COEFFICIENTS (ALFA) FOR 16 (NPOD) PODS. IT
C ALSO COMPUTES DEVIATION STATISTICS FOR THE FORECAST (MADEV = MEAN ABSOLUTE
C DEVIATION, MDEVSQ = MEAN DEVIATION SQUARED). DEVIATION STATISTICS FOR THE
C VARIOUS ALFA LEVELS ARE AGGREGATED THRU ALL PODS (TMAD AND TMADSQ).
C PROVISIONS FOR PLGTTING RESULTS ARE INCLUDED.
C ***** ONE (1) WEEK HORIZON *****
C INTEGER POD
C REAL MADEV, MDEVSQ
C DIMENSION VOL(52), DEV(52), DEVSQ(52), FCST(52), FCSTAV(52)
C DIMENSION CATRND(52), ATRNDA(52), POD(16)
C DIMENSION ALFA(11), MADEV(16,11), MDEVSQ(16,11)
C DIMENSION X(101), Y(101,4), TMAD(11), TMADSQ(11)
C DATA TMAD/11*0./, TMADSQ/11*0./
C DATA K/52/, NPOD/16/, NALFA/11/
C DATA ALFSTP/100./, NHORIZ/1/
C FORMAT(I3), 27X, F10.0)
1  FFORMAT(1), 4(VPOD ALPHA MADEV * ' ')
2  FFORMAT(1), 4(A3, F5.2, F8.0, F13.0, * '))
3  FFORMAT(1), 4(3X, F5.2, F8.0, F13.0, * '))
4  FFORMAT(1), 4(3X, F5.2, F8.0, F13.0, * '))
5  FFORMAT(1), 4(3X, F5.2, F8.0, F13.0, * '))
6  FFORMAT(1), 4(3X, F5.2, F8.0, F13.0, * '))
7  FFORMAT(1), 4(3X, F5.2, F8.0, F13.0, * '))
C READ A NUMBER (NA) TO INITIALIZE THE COMPUTATION OF ALFAS BY 100THS (ALFSTP)
C OVER A DESIRED RANGE (NALFA).
C READ(5,1) NA
C DO 9 L=1, NALFA
C ALFA(L)=(FLOAT(NA-L))/ALFSTP
9  CONTINUE
C DO 10 K=1, NPOD
C READ K WEEKLY TOTAL VOLUMES OBSERVED FOR A POD.
C DO 12 I=1, K
C READ(5,2) POD(N), VOL(I)
12 CONTINUE
C SET THE SMOOTHING CONSTANT LEVEL (ALFA) TO BE USED.
C DO 19 L=1, NALFA
C IF(ALFA(L).EQ.0) GO TO 18
C ZERO AND INITIALIZE WORKING VARIABLES.
C DO 13 I=1, K
C DEVSQ(I)=0.
C FCST(I)=0.
C FCSTAV(I)=0.
C CATRND(I)=0.
C ATRNDA(I)=0.
13 CONTINUE

```



```

TDEVSQ=0.
JJ=0
ALFA1=1.-ALFA(L)
FCSTAV(I)=VOL(I)
C START THE FORECAST GENERATION PROCEDURE.
DO 16 I=2,K
C SKIP THE DEVIATION CALCULATIONS IF THIS IS THE FIRST SET OF OBSERVATIONS AS
C THE FIRST FORECAST IS NOT YET COMPUTED.
IF(I.EQ.2) GO TO 15
C CALCULATE THE DEVIATIONS FROM THE FORECAST FOR THE CURRENT PERIOD.
C APPLY THE CURRENT FORECAST TO NHORIZ PERIODS.
DO 14 M=1,NHORIZ
J=I+NHORIZ-M
DEV(I)=DEV(I)+FCST(I)-VOL(J)
14 CONTINUE
DEV(I)=ABS(DEV(I)/FLOAT(NHORIZ))
DEVSQ(I)=DEV(I)**2.
TDEV=TDEV + DEV(I)
TDEVSQ = TDEVSQ + DEVSQ(I)
JJ=JJ+1
C SKIP THE FORECAST CALCULATION THAT WOULD APPLY THRU PERIOD K+1.
15 IF(I-1+NHORIZ.EQ.K) GO TO 17
C CALCULATE THE FORECAST FOR THE NEXT PERIOD INCLUDING TREND EFFECTS.
FCSTAV(I)=ALFA(L)*VOL(I) + ALFA1*FCSTAV(I-1)
CATRND(I)=FCSTAV(I)-FCSTAV(I-1)
ATRND(I)=ALFA(L)*CATRND(I)+ALFA1*ATRND(I-1)
FCST(I+1)=FCSTAV(I)+ATRND(I)/ALFA(L)
16 CONTINUE
C COMPUTE THE DEVIATION STATISTICS FOR THE POD AT THIS ALFA LEVEL.
17 MADEV(N,L)=TDEV/FLOAT(JJ)
MDEVSQ(N,L)=TDEVSQ/FLOAT(JJ)
GO TO 19
18 MADEV(N,L)=0.
MDEVSQ(N,L)=0.
19 CONTINUE
C AGGREGATE THE DEVIATION STATISTICS FOR THE ALFA LEVEL INTERVALS.
DO 70 N=1,NPOD
DO 70 L=1,NALFA
TMAD(L)=TMAD(L)+MADEV(N,L)
TMADSQ(L)=TMADSQ(L)+MDEVSQ(N,L)
70 CONTINUE
C ** INCLUDE AT THIS POINT A ROUTINE TO CALL FOR PLOTS OF ALFA LEVELS VS.
C EITHER DEVIATION STATISTIC FOR A POD. ORIGINALLY THIS THESIS USED THE
C SUBROUTINE OSPLOT AVAILABLE AT THE W. R. CHURCH COMPUTER CENTER, NAVAL
C POSTGRADUATE SCHOOL, MONTEREY, CAL. **
C
C ROUTINE FOR PLOTTING ALFA LEVELS VS PODS

```


C SET NX = NALFA OR NGAMMA DEPENDING OF FORECASTING METHOD

NX=NALFA

M=0

50 M=M+1

IF(M.GT.4) GO TO 20

DO 60 I=1,NX

J=NX+1-I

X(J)=ALFA(I)

DC 60 N=1,4

L=(M-1)*4+N

Y(J,N)=MADEV(L,I)

60 CONTINUE

NDIM=101

N=NDIM

NCUR=4

ISCALE=1

XLFT=-.1

XRT=.9

YLO=0.

YHI=9600.

CALL OSPLOT(X,Y,N,NDIM,NCUR,ISCALE,XLFT,XRT,YLO,YHI)

PRINT OUT TABLES OF AVERAGE WEEKLY DEVIATIONS FOR ALL ALFA LEVEL INTERVALS

C COMPUTED FOR EACH POD.

WRITE(6,3)

L=(M-1)*4+1

LL=M*4

WRITE(6,4) (POD(N),ALFA(I),MADEV(N,1),MDEVSQ(N,1),N=L,LL)

DO 61 I=2,NALFA

IF(I.EQ.70) WRITE(6,3)

WRITE(6,5) (ALFA(I),MADEV(N,I),MDEVSQ(N,I),N=L,LL)

61 CONTINUE

GO TO 50

C

20 CONTINUE

C PRINT OUT AGGREGATE DEVIATION STATISTICS FOR ALL ALFA LEVEL INTERVALS

C COMPUTED.

WRITE(6,6)

DO 25 I=1,NALFA

IF(I.EQ.70) WRITE(6,6)

WRITE(6,7) ALFA(I),TMAD(I),TMADSQ(I)

25 CONTINUE

STOP

END


```

GAMMA=1.-GAMMA(L)
FCSTAV(I)=VOL(I)
FCST(2)=VOL(I)
KEND=K+1-NHORIZ
START THE FORECAST GENERATION PROCEDURE.
DO I=2,KFND
SKIP THE DEVIATION CALCULATIONS IF THIS IS THE FIRST SET OF OBSERVATIONS AS
THE FIRST FORECAST IS NOT YET COMPUTED.
IF(I.EQ.2) GO TO 15
CALCULATE THE DEVIATIONS FROM THE FORECAST FOR THE CURRENT PERIOD.
APPLY THE CURRENT FORECAST TO NHORIZ PERIODS.
DO I4 M=1,NHORIZ
J=I+NHORIZ-M
DEV(I)=DEV(I)+FCST(I)-VOL(J)
14 CONTINUE
DEV(I)=ABS(DEV(I)/FLOAT(NHORIZ))
DEVSQ(I)=DEV(I)**2.
TDEV=TDEV + DEV(I)
TDEVSQ = TDEVSQ + DEVSQ(I)
JJ=JJ+1
SKIP THE FORECAST CALCULATION THAT WOULD APPLY THRU PERIOD K+1.
IF(I.EQ.KEND) GO TO 17
COMPUTE THE ALFA LEVEL TO BE USED BY SMOOTHING THE ERRORS THAT OCCURRED IN
THE CURRENT PERIOD.
15 ERR=VOL(I)-FCST(I)
AERR=ABS(ERR)
SERR(I)=GAMMA*SERR(I-1)+GAMMA(L)*ERR
SAERR(I)=GAMMA*SAERR(I-1)+GAMMA(L)*AERR
IF(SAERR(I).EQ.0) GO TO 18
ALFA=ABS(SERR(I)/SAERR(I))
IF(ALFA.EQ.0) GO TO 18
ALFA=1.-ALFA
CALCULATE THE EXPONENTIALLY WEIGHTED AVERAGE (FCSTAV) AND FORECAST (FCST)
FOR THE NEXT PERIOD.
FCSTAV(I)=ALFA*VOL(I) + ALFA*FCSTAV(I-1)
FCST(I+1)=FCSTAV(I)
16 CONTINUE
COMPUTE THE DEVIATION STATISTICS FOR THE POD AT THIS GAMMA LEVEL.
17 MADEV(N,L)=TDEV/FLOAT(JJ)
MDEVSQ(N,L)=TDEVSQ/FLOAT(JJ)
GO TO 19
18 MADEV(N,L)=0.
MDEVSQ(N,L)=0.
19 CONTINUE
AGGREGATE THE DEVIATION STATISTICS FOR THE GAMMA LEVEL INTERVALS.
DO L=1,NGAMMA
DO N=1,NPOD
TMAD(L)=TMAD(L)+MADEV(N,L)

```



```

C C TMADSQ(L)=TMADSQ(L)+MDEVSQ(N,L)
C C 70 CONTINUE
C C ** INCLUDE AT THIS POINT A ROUTINE TO CALL FOR PLOTS OF GAMMA LEVELS VS.
C C EITHER DEVIATION STATISTIC FOR A POD. ORIGINALLY THIS THESIS USED THE
C C SUBROUTINE USPLOT AVAILABLE AT THE W. R. CHURCH COMPUTER CENTER, US NAVAL
C C POSTGRADUATE SCHOOL, MONTEREY, CAL. **
C C
C C ROUTINE FOR PLOTTING GAMMA LEVELS VS PODS
C C SET NX = NALFA OR NGAMMA DEPENDING OF FORECASTING METHOD
C C NX=NGAMMA
C C NDIM=NX
C C NCUR=4
C C ISCALE=1
C C XLFT=-1.
C C XRT=1.
C C YLO=0.
C C YHI=9600.
C C DO 49 I=1, NX
C C J=NX+1-I
C C X(J)=GAMMA(I)
C C 49 CONTINUE
C C M=0
C C 50 M=M+1
C C IF(M.GT.4) GO TO 20
C C DO 60 I=1, NX
C C J=NX+1-I
C C DO 60 N=1,4
C C L=(M-1)*4+N
C C Y(J,N)=MADEV(L,I)
C C 60 CONTINUE
C C N=NDIM
C C CALL OSPLT(X, Y, N, NDIM, NCUR, ISCALE, XLFT, XRT, YLO, YHI)
C C PRINT OUT TABLES OF AVERAGE WEEKLY DEVIATIONS FOR ALL GAMMA LEVEL INTERVALS
C C COMPUTED FOR EACH POD.
C C WRITE(6,3)
C C L=(M-1)*4+1
C C LL=M*4
C C WRITE(6,4) (POD(N), GAMMA(1), MADEV(N,1), MDEVSQ(N,1), N=L, LL)
C C 61 I=2, NGAMMA
C C IF(I.EQ.70) WRITE(6,3)
C C IF(I.EQ.140) WRITE(6,3)
C C WRITE(6,5) (GAMMA(I), MADEV(N,I), MDEVSQ(N,I), N=L, LL)
C C 61 CONTINUE
C C GO TO 50
C C
C C 20 CONTINUE

```



```

C PLOT GAMMA LEVELS VS. AGGREGATE DEVIATION STATISTICS.
DO 80 I=1,NX
J=NX+1-I
Y(J,I)=TMAD(I)
80 CONTINUE
N=NDIM
NCUR=1
YLO=46000.
YHI=71600.
CALL DSPLLOT(X,Y,N,NDIM,NCUR,ISCALE,XLFT,XRT,YLO,YHI)
C PRINT OUT AGGREGATE DEVIATION STATISTICS FOR ALL GAMMA LEVEL INTERVALS
COMPUTED.
WRITE(6,6)
LN=NGAMMA/3
DO 25 I=1,LN
J=LN+I
L=2*LN+I
WRITE(6,7) GAMMA(I), TMAD(I), TMADSQ(I), GAMMA(J), TMAD(J),
TMADSQ(J), GAMMA(L), TMAD(L), TMADSQ(L)
1
25 CONTINUE
STOP
END

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